Biased Teachers and Gender Gap in Learning Outcomes: Evidence from India

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Abstract

This paper investigates the effect of stereotypical beliefs of teachers on learning outcomes of secondary school students in India. We measure teacher's bias through an index capturing teacher's subjective beliefs about the role of gender and other characteristics in academic performance. We tackle the potential endogeneity of teacher's subjective beliefs by controlling for teacher fixed effects in a value-added model that includes lagged test score of students. We find that a standard deviation increase in biased attitude of the math teacher widens the female disadvantage in math performance by 0.07 standard deviation over an academic year. This negative effect of biased teachers is significant only for male teachers. The effect is especially strong among the medium-performing students and in classes where the majority of students are boys. Moreover, among the medium-performing students, having a female teacher significantly reduces the gender gap in math performance. As a plausible mechanism, we show that biased teachers negatively affect girls' attitude towards math as compared to boys. Unlike math outcome, we do not find any significant effect when we analyze the effect of biased English teachers on English scores of the same students.

Keywords: Learning outcomes; Value-added model; Gender; Teachers; Stereotypes; India

JEL codes: I24; J16; J24

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1 Introduction

Over the last few decades there has been substantial progress in bridging the gender gap in educational attainment all over the world. In developing countries, the gender gap in school enrollment has practically disappeared; hence, the policy discourse has gradually focused more on the quality aspects of education.[1] While participation of girls in education has substantially increased over time, gender gap has persisted in various other forms.[2] Underperformance of girls in mathematics, especially in their adolescent age, is a long-standing issue that has been widely documented in the literature (Benbow and Stanley, 1980; Fryer and Levitt, 2010; Bharadwaj et al., 2016). At the same time, underrepresentation of girls in science, technology, engineering and mathematics (STEM) has been pervasive (Kahn and Ginther, 2017). Gender inequality in math performance and STEM participation may further lead to occupational segregation and gender pay gap in the labour market, impacting the overall economic outcomes of women relative to men (World Bank, 2012; Joensen and Nielsen, 2016).

In this paper, we analyze the role of teachers in determining the gender gap in learning outcomes. In particular, we investigate how the biased and stereotypical beliefs of teachers cause gender gap in math performance of secondary school students. We use matched student-teacher level data collected by the Young Lives survey from 205 schools across two states in India to estimate a value-added model of education production function. To capture a teacher's biased attitude, we use an index of the teacher's subjective beliefs about the role of gender and other characteristics in academic performance. Two aspects of our empirical strategy help us to alleviate the concern of endogeneity issues. First, we use a value-added model that includes the baseline test score of students. Second, we include teacher fixed effects to control for all observable and unobservable characteristics of the teachers and schools. Thus, our identification strategy is based on a comparison of the value-added in test scores of girls versus boys taught by the same

[1] The post-2015 agenda of the UN Sustainable Development Goals target providing equal access to good quality education to both boys and girls.

[2] For example, gender gap in private versus government school choice has emerged with the rise in private schooling (Sahoo, 2017).

teacher, between biased and unbiased teachers. We also provide supporting evidence indicating that there is no systematic assignment of students based on their ability or gender to teachers with different levels of biased beliefs.

We show that there is a significant gender gap in mathematics achievement among secondary school students, and this gap increases over an academic year. We find that a standard deviation increase in teacher's biased attitude widens the gender gap in math score by 0.07 standard deviation over the academic year. We further show that this negative effect is significant only for biased *male* teachers. On the other hand, being taught by a female math teacher significantly reduces the gender gap in math performance among the medium-performing students. We also find that girls are negatively impacted by biased teachers especially when they study in a male-dominated classroom. Besides, we show that the effects emanate from teachers' gender-stereotypical beliefs rather than bias related to other dimensions such as caste and class.

To understand the potential mechanisms, we explore the effect of the teacher's gender and biased beliefs on students' self-reported attitude towards math, particularly on dimensions related to math importance, interest, and dislike. We find that girls, in comparison with boys, tend to develop a negative attitude towards math when they are taught by a male teacher who holds stereotypical beliefs about girls' ability to do well in studies. Our mediation analysis shows that around 10 percent of the total effect of biased teachers is channeled through the effect on students' attitude towards math. We do not find any significant effect of teachers' gender or their biased beliefs on language outcome. These results hold up to a battery of robustness tests considering alternative measures of teacher's bias and sample selection issues.

Our paper contributes to multiple strands of the existing literature. First, our findings relate to various studies documenting the gender gap in math performance and its causes (Fryer and Levitt, 2010; Bharadwaj et al., 2016; Nollenberger et al., 2016). More specifically, we contribute to a smaller body of recent literature showing that the biased and stereotypical attitude of teachers is an important factor in explaining the gender gap in STEM (Alan et al., 2018; Lavy and Sand, 2018; Carlana, 2019; Lavy and

Megalokonomou, 2019). Our estimates from a value-added model using data from a developing country complement the existing evidence on this issue.[3] Moreover, by utilizing independently collected test scores as outcome measures, we evaluate the impact of teacher's bias on actual learning outcomes. Thus, our analysis is different from some other studies in the literature that look at discrimination in grading induced by teacher's biased beliefs (Lavy, 2008; Lavy and Sand, 2018; Terrier, 2020).

Our results indicate that the effect of biased teachers on gender gap depends on the gender of the teacher. Thus, we also add to the literature exploring the effect of teacher's gender on learning outcomes (Dee, 2007; Paredes, 2014; Muralidharan and Sheth, 2016; Lim and Meer, 2017; Xu and Li, 2018; Lee et al., 2019). Evidence from these studies suggests that female teachers may have a positive role-model effect on girls while being as effective as male teachers in teaching boys. Our results also indicate that female teachers are instrumental in closing the gender gap among students who are in the middle part of the baseline ability distribution. The finding that female teachers, even when they have the same levels of biased attitudes as male teachers, do not have any significant negative impact suggests that their positive role-model effect off-sets the negative effect of stereotype. By taking these two dimensions together in the analytical framework, we also contribute to understanding the mechanisms behind the effect.

More broadly, we contribute to the wide literature on gender disparity in education outcomes in developing countries. While most of this literature so far has analyzed household level factors or access to education, our paper relates to a few studies that explore the role of teachers in girls' education (Rawal et al., 2010; Lee et al., 2019). In the context of USA, Hanushek (2011) and Chetty et al. (2014) show that teacher quality has far-reaching influence on adult-life earnings of students. Biased attitude is an important aspect of teacher quality that impacts the mathematical skill development of girls at the secondary level of education which is crucial for subsequent education choices and economic outcomes in the later life (Murnane et al., 2000; Sahoo and Klasen, 2020). This

[3] Other studies in the recent literature on teacher's stereotypical attitude, e.g. Alan et al. (2018) on Turkey and Carlana (2019) on Italy, have relied on quasi-random assignment of teachers to classes and the use of fixed effects for identification. We additionally utilize the value-added framework, as discussed in detail in Section 4.1.

is especially relevant in the context of India where female labour force participation is very low and it is crucial to develop human capital of girls in order to reap the benefit of a demographic dividend (Klasen and Pieters, 2015; Sarkar et al., 2019).

Our study also has implications for policy makers. In countries like India where gender bias is pervasive in the society, some studies have suggested that gender sensitization program for adolescent school-going students may be beneficial for promoting gender equality (Dhar et al., 2018). We show that there is also a need for sensitizing teachers, perhaps through the institution of in-service teacher training, in order to achieve gender equality in learning outcomes.

The rest of the paper is organized as follows. In section 2, we discuss the relevant literature. Section 3 describes the dataset, main variables, and summary statistics. Section 4 explains the empirical model. Results of analysis are discussed in section 5. Section 6 concludes the paper.

2 Background and Related Literature

The persistent gender gap in math performance and STEM participation has motivated many studies to investigate the mechanisms that drive such outcomes. A long-standing literature has identified the female disadvantage in mathematics outcomes in various parts of the world (Benbow and Stanley, 1980; Fryer and Levitt, 2010; Nollenberger et al., 2016). In developing countries, with rising school participation and diminishing gender gap in enrollment rates, the recent discourse has focused more on gender equality in access to good quality education and learning outcomes. Against this backdrop, some studies have pointed out the existence of gender gap in learning outcomes that shows up especially at the adolescent ages. For instance, Singh and Krutikova (2017) analyze child level panel data from four developing countries (including India) and find that gender gaps in learning are nonexistent at pre-school and early primary levels but are evident in the period of post-primary schooling. Especially in mathematics achievement, various other studies such as Fryer and Levitt (2010) in the context of USA and Bharadwaj et al.

(2016) in the context of Chile have also documented that pro-male gender gap widens as children grow older. The female disadvantage in mathematics may be closely linked with under-representation of women in math-intensive STEM fields and subsequent labour market outcomes (Kahn and Ginther, 2017; Sahoo and Klasen, 2020).

The extant literature has explored the role of teachers in this context. A number of studies have analyzed the impact of teacher's gender and found female teachers to be effective in reducing the gender gap in education outcomes (Dee, 2007; Paredes, 2014; Lim and Meer, 2017; Xu and Li, 2018; Lee et al., 2019). Some other studies have found no such effect (Holmlund and Sund, 2008; Cho, 2012), or small effects (Winters et al., 2013), or indicated that the effect may depend on teacher's content knowledge (Antecol et al., 2015).[4] Close to the context of this study, Muralidharan and Sheth (2016) find that both male and female teachers are more effective at teaching students of their own gender in primary schools of Andhra Pradesh, a state in India. However, they also find that female teachers are more effective overall, resulting in girls' test scores improving by an additional 0.036 standard deviation per year when they are taught by a female teacher, with no adverse effects on boys. This study suggests that recruiting female teachers can be an effective policy to improve girls' learning outcome in developing countries.

There is also evidence that the gender gap in learning outcomes is significantly affected by social attitudes towards girls' education and by other forms of gender discrimination in society at large (Bandyopadhyay and Subrahmanian, 2008). In this regard, the gender gap in learning is further aggravated if such stereotypical beliefs are held by teachers. If teachers hold biased beliefs about the learning abilities of girls vis-à-vis boys, they may fail to be impartial while teaching students of both genders and this may hamper girls' performance (Glover et al., 2017; Bohren et al., 2019). Girls taught by teachers with traditional gender views may have lower performance in objective math and verbal tests and this effect may be amplified with longer exposure to the same teacher (Alan

[4] Rawal et al. (2010) find that learning outcomes are positively affected when there is a teacher-student matching based on gender, caste, and religion in primary schools in two northern states of India.

et al., 2018). The potential negative effect on girls' performance is particularly relevant in mathematics which is traditionally associated with boys. Using Gender Science Implicit Association Test score as a measure of teacher's implicit stereotype, Carlana (2019) finds that the gender gap in math performance substantially widens when students are taught by math teachers with stronger gender stereotypes.[5] As an underlying mechanism, exposure to biased teachers may reduce girls' self-confidence as a result of confirming to the negative self-stereotypes causing them to underperform in maths (Spencer et al., 1999).

Insofar as the teacher's biased beliefs and behaviour affects math learning of girls, it may have long run implications for subsequent field choice and adult labour market outcomes because participation in STEM fields requires prior knowledge in mathematics (Lavy and Sand, 2018). Indeed, a few studies show that school level exposure to biased teachers significantly affects field choices at the subsequent levels of education (Lavy and Megalokonomou, 2019; Carlana, 2019). In this context, being taught by a female teacher may have a motivating effect on girls and that may extend to a higher likelihood of girls choosing a STEM degree in the future (Bottia et al., 2015; Solanki and Xu, 2018; Lim and Meer, 2019).

The possibility that teachers' views and attitudes in the classroom reflect the gender norms prevailing in the society at large makes the relationship between teacher's gender and student's learning more nuanced. Sansone (2017) finds that teacher's gender matters because male and female teachers differ in their gender-related math and science attitudes and how they treat male and female students. Bassi et al. (2018) show that teachers in Chile give more attention to and interact more with boys and this behaviour is associated with a larger gender gap in math score. This evidence suggests that while

[5] Alesina et al. (2018) have also studied teacher's assessment bias in differentially grading immigrants and native children in middle school. They find that math teachers with stronger stereotypes give lower grades to immigrants compared to natives with the same performance. Further, Copur-Gencturk et al. (2020) conducted a randomized controlled study to distinguish between teachers' accurate assessments of students' ability and their implicit bias. They found that teachers displayed no detectable bias when assessing the mathematical solutions of fictitious students, but gender- and race-associated biases were revealed in estimating the mathematical ability of students with partially correct and incorrect responses.

interpreting the effect of teacher-student gender matching on learning outcomes, it is imperative to consider teacher's attitude which may be correlated with teacher's gender as well as how teachers treat boys and girls in the class. Investigating the channels through which a female teacher benefits girls, Paredes (2014) shows that the benefit is due to a role-model effect rather than teacher bias effects. In this paper, we separate out the effect of teacher's bias from gender by including both the measures in the regression.

3 Data and Descriptive Analysis

The data used for this paper are from a secondary school survey conducted by Young Lives in India in 2016-17.[6] The primary objective of the survey was to gain insights on the quality of education and understand the effectiveness of secondary schooling in the Indian states of Andhra Pradesh and Telangana. The Young Lives study collected data from classroom surveys of ninth-grade students across seven districts in these two states.[7] Data on students' test scores were collected in two rounds, one at the start of the school year (July-August 2016) and the other during the end of the school year (January-March 2017) from approximately 9,000 students in 205 schools.[8] This method of data collection aided in understanding the progress of students' performance over the course of an academic year. The survey also collected information on the background characteristics including psychosocial skills of students and teachers.

Young Lives designed the cognitive tests keeping in mind its contextual relevance in the study-country. The survey administered mathematics and functional English tests at the beginning and end of the school year (wave 1 and wave 2 of data collection

[6] Young Lives is a study of child poverty in India, Peru, Ethiopia and Vietnam. In 2002, the study started following the lives of about 12,000 children (in two cohorts) in these four countries through household surveys. Details can be found at www.younglives.org.uk. In addition to the household surveys, Young Lives introduced school surveys in 2010 in all the four countries.

[7] The survey was done in secondary schools in 20 Young Lives sites (used for household surveys) which were spread across the seven districts in the two states.

[8] A total of 9820 students were covered in the baseline; out of them we have information on the math score for 9574 students and English score for 9596 students. All the students in a class were included in the data. Test scores were collected in the endline for the same students; however, there is around 16 percent attrition. In a robustness analysis, we show that our estimates are not susceptible to attrition bias.

respectively). Young Lives used TIMSS Math Assessment Framework as an effective procedure to evaluate student's mathematical ability in secondary school. The math content domains were developed using school curriculum for the ninth-grade students in India. The total pool of questions was developed through the careful analysis of a pilot survey using Classical Test Theory and Item Response Theory before the final selection of test items for the two waves of survey. The cognitive tests conducted at the beginning and end of the school-year used repeated measures and were linked so that students' progress over the school-year could be effectively captured (Moore et al., 2017).

The outcome variable of interest is the math and English scores (number of items the student got correct) in both the rounds. For our analysis, we standardize the scores making the mean 0 and variance 1. Given the importance of math learning and its relation to gender as pointed out in the literature, we focus on math for the main analysis and present the equivalent results for English learning in section 5.5. Figure 1 plots the distribution of standardized math score for boys and girls, both at baseline and endline. We find a statistically significant gender gap in the mean math score; a Kolmogorov-Smirnov test reveals that the distributions are also significantly different – girls underperform in math and this gap is larger in the endline (0.165 standard deviation) as compared to the baseline (0.108 standard deviation).

The data has matched student-teacher level information for both math and English. A crucial aspect of the Young Lives school survey in India is that each teacher is asked a set of questions related to their subjective beliefs about how students' gender, caste, and class affect their learning outcomes. The responses to these questions are recorded in a four-level Likert scale indicating how strongly the teacher agrees with statements such as "boys are able to do better in studies than girls" (Table 1). The first two questions are related to the perception about gender; the last two questions are about caste and class, respectively.[9] We create an index out of these responses using a Graded Response Model which is an extension of the Item Response Theory considering responses that are in a Likert-type scale (Raykov and Marcoulides, 2018). In a later analysis, we also

[9]The Cronbach's alpha measuring the internal consistency of these items is 0.72.

separately analyze the effect of gender-stereotype by constructing the index taking only the questions related to gender. The index of teacher's bias is standardized to have mean 0 and variance 1. Figure 2 plots the distribution of the index separately for male and female math teachers. Summary statistics of other variables used in the analysis are presented in Table 2-3.

Appendix Table A1 presents the correlation between our measure of teacher's bias and several observable characteristics of teachers. We find no association between teacher's bias and observable characteristics such as gender, social category, age, teaching experience or salary of the teacher. Interestingly, highly educated teachers (having a master's degree) do not seem to be more or less likely to have stereotypical beliefs against student's gender, caste or class. Teachers who are able to use English for conversation purpose seem to be less biased and so are teachers with a higher asset index. Teachers who have a permanent contract (as opposed to fixed-term contract) and those who work full-time (as compared to part-time) are less likely to be biased. Again, teachers of state government schools, rather than private schools, have lesser stereotypical beliefs against students. The findings are robust to the inclusion of district fixed effects.

4 Empirical Strategy

The main estimating equation of our analysis is a value-added model of mathematics score as given in Equation (1).

$$\begin{aligned} MathScore_{ijs} = \alpha_0 + \alpha_1 BaselineMath_{ijs} + \alpha_2 GirlStudent_{ijs} + \alpha_3 BiasedTeacher_{js} \\ + \alpha_4 FemaleTeacher_{js} + \alpha_5 X_{ijs} + \alpha_6 Z_{js} + \varepsilon_{ijs} \end{aligned} \tag{1}$$

The outcome variable denotes the standardized math score of student i taught by teacher j in school s. The outcome is measured at the end of the academic year of students in ninth grade. In accordance with a value-added specification, we include the baseline math score as a control variable ($BaselineMath$) which is measured at the beginning of the academic year. $GirlStudent$ is a binary indicator of whether the student is a girl. Additional student specific characteristics such as age, caste, parental education, and location specific indicators (rural or urban residence and district dummies) are included in the vector X.

Since we have a matched student-teacher data, therefore we are able to include variables reflecting the characteristics of the teacher who have taught the students in the same academic year. The main variable we are interested in is a measure of teacher's bias given by $BiasedTeacher$. This is a continuous measure obtained by applying Item Response Theory – Graded Response Model to the four different variables capturing teacher's stereotype against gender, caste, and class, as discussed in the earlier section. The variable reflects the latent bias of the teacher and it is standardized to have mean 0 and variance 1. In the robustness section, we also present results separately for gender related bias versus caste and class related bias of the teacher. The gender of the math teacher is given by the binary variable $FemaleTeacher$ which takes the value 1 if the teacher is female and 0 if the teacher is male. The vector Z includes other teacher specific observable characteristics, such as teacher's age, caste, professional background (qualification and training), type of contract (permanent versus temporary), whether the teacher is head-teacher, whether the teacher can converse in English, and whether the teacher does any other supplementary activity apart from teaching.

Equation (1) can be viewed as a dynamic ordinary least squares model where the lagged test score is supposed to capture the effect of all previous inputs as well as unobservable endowments and shocks (Todd and Wolpin, 2007). The value-added model has been used by Singh (2015) in a similar context to estimate the causal effects of private versus public schooling on test scores. We use Equation (1) to identify the gender gap in mathematics achievement, given by the coefficient α_2, that evolves through the course of grade nine for the students in the sample. Further, we estimate whether there is any effect of being taught by a teacher who is biased (α_3) and of being taught by a female teacher as opposed to a male teacher (α_4).

In the next step, we improve our empirical specification in two ways. First, we consider the possibility that the teacher's stereotypical beliefs may have a differential effect on boys and girls; therefore, we include an additional interaction term between the teacher-bias variable and gender of the student. Second, we take into account the possibility of endogeneity in the teacher related variables. It is possible that the matching between teachers and students is non-random; for instance, better quality teachers may be assigned to teach better-performing students who may have different learning trajectories than worse-performing students. Some of these effects are captured through lagged test score, but that is not adequate to control for any differential learning trajectories based on ability of the student. Further, since the measure of teacher's bias is based on self-reported responses, it may be correlated with teachers' unobserved tastes and preferences. Although Equation (1) includes control variables at the level of students as well as teachers, there may still be unobserved characteristics which are omitted from the model. To address these concerns, we include teacher fixed effects (ϕ_{js}) in the regression. Since a teacher does not teach in more than one school, rather a school may have multiple teachers teaching different sections, therefore school fixed effects (ψ_{js}) are subsumed by teacher fixed effects. This mitigates the concern of endogeneity due to sorting of students into different schools on the basis of ability. Hence, our next model is an augmented version of the last model:

$$\begin{aligned} MathScore_{ijs} = {} & \beta_0 + \beta_1 BaselineMath_{ijs} + \beta_2 GirlStudent_{ijs} + \beta_3 BiasedTeacher_{js} \\ & + \beta_4 FemaleTeacher_{js} + \beta_5 GirlStudent_{ijs} \times BiasedTeacher_{js} \\ & + \beta_6 X_{ijs} + \beta_7 Z_{js} + \phi_{js} + \psi_s + \varepsilon_{ijs} \end{aligned} \tag{2}$$

In Equation (2), the coefficient of the interaction term (β_5) gives the differential effect of teacher's bias on girls versus boys, thus a negative coefficient would imply that biased teachers hurt the learning outcomes of girls more than boys. Inclusion of teacher fixed effects implies that we cannot separately identify the effect of observable characteristics of teachers, such as $FemaleTeacher$ or $BiasedTeacher$. However, we can identify the differential effect of these characteristics on the gender gap in students' learning outcome.[10] In the final specification, we further augment the model by including triple interaction between teacher's gender, student's gender, and teacher's bias:

$$\begin{aligned} MathScore_{ijs} = {} & \gamma_0 + \gamma_1 BaselineMath_{ijs} + \gamma_2 GirlStudent_{ijs} \\ & + \gamma_3 BiasedTeacher_{js} + \gamma_4 FemaleTeacher_{js} \\ & + \gamma_5 GirlStudent_{ijs} \times BiasedTeacher_{js} \\ & + \gamma_6 GirlStudent_{ijs} \times FemaleTeacher_{js} \\ & + \gamma_7 BiasedTeacher_{js} \times FemaleTeacher_{js} \\ & + \gamma_8 GirlStudent_{ijs} \times BiasedTeacher_{js} \times FemaleTeacher_{js} \\ & + \gamma_9 X_{ijs} + \gamma_{10} Z_{js} + \phi_{js} + \psi_s + \varepsilon_{ijs} \end{aligned} \tag{3}$$

Equation (3) allows us to investigate two additional hypotheses. The first hypothesis is whether female teachers affect gender gap in learning, reflected by γ_6. The second hypothesis is whether the effect of biased teachers on gender gap depends on the gender of the teacher; this is given by the coefficient of the triple interaction term, γ_8. The coefficients γ_3, γ_4, and γ_7 cannot be separately identified from the teacher fixed effects, hence they are not reported in the results.

4.1 Discussion on Identification

In analyzing the causal effect of teacher bias on student outcome, the main challenge is to address the potential non-random matching between teachers and students. The empirical strategy laid out in Equations (2) and (3) utilizes the value-added framework with teacher fixed effects to identify the impact of teacher's stereotypical attitude on the gender gap in test score. The inclusion of teacher fixed effects ensures that any teacher-level factor, including the average quality of students taught by the teacher, is taken into account. It is possible that better quality teachers are assigned to teach better quality students. Parents of high-performing students may also select schools that have

[10] In a robustness analysis presented later, we additionally include all the student and teacher characteristics (X_{ijs} and Z_{js}) interacted with the gender of the student.

better quality teachers. Although in the Indian context such selections are unlikely to be on the basis of teachers' stereotypical attitude, teachers' attitude may be correlated with their quality.

We directly examine if students are sorted based on ability or gender to be taught by biased teachers. We regress the index of teacher bias on the baseline characteristics of the students taught by the teacher, with a focus on the average baseline math score and the proportion of girls. Results presented in Table A2 show that there is no significant relationship between teacher bias and students' baseline test score or gender. While teacher fixed effects would anyway subsume these factors, it is reassuring to find evidence suggesting that girls or worse performing students are not systematically assigned to be taught by teachers with stronger or weaker stereotypical attitude. An additional concern is whether girls are differentially sorted than boys based on their ability.[11] To investigate this issue, we include an interaction between the baseline test score and the proportion of girls in the same regression (columns 2-5, Table A2). We also estimate another set of regressions where the average baseline scores are included separately for boys and girls, considering teachers who have taught students of both genders (columns 6-9, Table A2). Across different specifications where control variables are gradually added, we do not find any evidence of gender-differentiated grouping of students based on their initial ability.[12]

Finally, note that our value-added model, by including the baseline test score, controls for individual-level variation in the quality of students.[13] This also further alleviates the concern of reverse causality where teachers may endogenously form their beliefs by

[11] If sorting based on ability varies by gender of the student, then that will induce within-teacher variation which will not be absorbed by the teacher fixed effects.

[12] We conduct a similar analysis for the assignment of female teachers. There, we find that female teachers are more likely to teach girls and low performing students; however, these effects die down once we include more control variables (Table A3).

[13] Our identification strategy is similar to the analysis by Alan et al. (2018) and Carlana (2019) who also explore the effect of gender-stereotyping by teachers on students' learning in the context of Turkey and Italy, respectively. Identification in both these papers relies on quasi-random assignment of teachers to students and inclusion of fixed effects. While Carlana (2019) includes class-level fixed effects (similar to teacher fixed effects in our model), Alan et al. (2018) controls for school fixed effects. However, none of these papers controls for lagged test score; in that sense, the value-added model (with teacher fixed effects) that we estimate is an improved specification.

observing the performance of the students. Since the baseline score takes into account the observed difference in the level of students' performance, teachers must form beliefs based on differential learning trajectories of boys and girls for reverse causation to be a concern. In a robustness test presented in section 5.2.5, we further interact gender of the student with all other student and teacher level observable characteristics. Thus, we consider the possibility that girls have a different learning trajectory based on the initial score (and other covariates) and differentially respond to various teacher characteristics than boys. As we discuss later, the results hold up to this robustness test.

5 Results

5.1 Main Results

The result of our main regression analysis is presented in Table 4. The first column of this table presents the basic model without any interaction term, as illustrated by Equation (1). We find that there is a significant positive effect of the baseline score on student's math achievement at the end of the academic session. The statistically significant and negative coefficient of the gender of the student implies that girls perform worse than boys in math outcome. This result is consistent with the literature which identifies gender gap in math performance among adolescent girls in many parts of the world. As pointed out by various studies, this could be due to continual underinvestment on girls' education from the childhood. Other psychosocial factors leading to girls' lack of confidence in mathematics, often termed as "mathematical anxiety", could also be a plausible reason behind this finding. We also find that students taught by female teachers score significantly lower than those taught by male teachers. However, this specification only controls for observable characteristics of teachers and hence we cannot rule out the possibility of endogenous matching between teachers and students. In particular, it is possible that female teachers are assigned to teach worse learners, thus the coefficient may not capture the causal effect of female teachers. We take this problem into account in a later specification.

The effect of a biased teacher is found to be statistically insignificant in the first model, although the sign of the coefficient is negative. The second column of Table 4 presents a regression that includes an interaction term between biased teacher and the gender of the student. This shows that while biased teachers do not affect the math performance of boys, they do negatively affect the outcome of girls. Thus, the gender gap in math performance significantly worsens when students are taught by a biased math teacher. To further investigate if this effect is causal, we include school and teacher fixed effects in our next specification presented in the third column of Table 4. Since the teacher fixed effects would absorb all the variation in any other characteristics of teachers, we are unable to identify the effect of biased teachers on boys and girls separately, but we can identify the effect on the gender gap. The coefficient of the interaction term remains statistically significant and negative, implying that a standard deviation increase in teacher's bias would reduce the math score of girls by about 0.07 standard deviation with respect to boys.

Our estimated effect size of 0.07 standard deviation is slightly higher than what Carlana (2019) finds in the context of Italy where a standard deviation increase in the "implicit bias" of teachers leads to a 0.03 standard deviation increase in the gender gap in students' math performance. Our results suggest that the harmful effect of teacher's bias is likely to be stronger in the context of a developing country like India where the society is plagued by various forms of gender inequality. To put this effect size in broader perspective, we compare it with the distribution of effect sizes found in various educational interventions in the literature. Covering several hundreds of educational interventions, Kraft (2020) for high-income countries, and Evans and Yuan (2020) for low- and middle-income countries, show that the median effect size for math outcome is 0.07 standard deviation. Thus, our estimated effect of biased teachers on gender gap in math outcome is the same as this median effect size reported in these papers synthesizing the existing evidence. Another way of interpreting this effect is to compare it with the baseline gender gap in math score which is 0.108 standard deviation, indicating that the effect of biased teachers is about 70 percent of the baseline gender gap in this context.

Is there a differential effect of biased teachers depending on the gender of the teacher? Recent literature shows that female teachers have a positive effect on the learning outcomes of girls. For example, Muralidharan and Sheth (2016) show that female teachers bridge the gender gap in learning outcomes, possibly because they are more empathetic towards girls and have a role-model effect. If this is true in our context, the negative effect of being biased may be off-set by the positive effect of being a female teacher. To test this hypothesis, we include the triple-interaction between student's gender, teacher's bias, and teacher's gender in the regression, as specified by Equation (3). The results are presented in the first column of Table 5. The coefficient of the interaction between girl student and biased teacher is negative and statistically significant. This term captures the effect of male teachers, since the model includes the triple interaction term involving teacher's gender. The coefficient of the triple interaction term is positive but statistically insignificant. The sum of these two coefficients, which captures the effect of biased *female* teachers on gender gap in math score, is negative but statistically not significant. Therefore, the negative effect of biased teachers on gender gap in math performance is significant only when the teacher is a male. We get the same conclusion from estimating the regression separately for male and female teachers, as shown in columns 2 and 3 of Table 5.

5.2 Robustness Analysis

5.2.1 Considering Attrition

In the robustness analysis, we first consider the potential bias due to attrition between the two waves of survey. The main analysis presented above employs a value-added model that controls for lagged score in a dynamic OLS framework. This requires the analysis to be based on students for whom we have test scores from both wave 1 (i.e. beginning of the academic session) and wave 2 (i.e. end of the academic session). However, between the first and the second wave of the survey, there is about 16 percent attrition. If students' attrition is correlated with the teacher's attitude, then it may lead to sample selection bias. To address this problem, we estimate the model using the inverse probability weighting technique (Wooldridge, 2010). The result remains unchanged, as shown in column 1 of Table 6.

5.2.2 Mixed-sex Classes

Next, we test the sensitivity of our estimates when we restrict the sample to students in mixed-sex classes. An important aspect of our identification strategy is the inclusion of teacher fixed effects to control for teacher specific unobserved heterogeneity. Identification in this model relies on comparison between students of opposite gender who are taught by the same teacher. If a school practices tracking by student's gender, then the comparison is made between boys and girls who study in different sections but are taught by the same math teacher.[14] In this case, a biased teacher may exert lesser effort while teaching the girls' section and thus it may lead to a gender gap in math learning. On the other hand, if our findings hold even in a co-educational setting, that would indicate that girls are negatively affected by biased teachers even when boys and girls are exposed to the same teaching environment.[15] The second column of Table 6 shows that the result holds even when we restrict the sample to co-educational classes.

5.2.3 Alternative Construct of Teacher's Bias

Further, we use alternative techniques to measure the main explanatory variable. Column 3 of Table 6 presents the estimates when the index of teacher's bias is constructed following the methodology of Alan et al. (2018). The estimates are comparable to our previous results.[16]

[14] The sample has only 5 teachers who teach multiple single-sex sections with students of opposite gender. Therefore, we do not estimate the regression separately for this sub-sample.

[15] Thus, this regression is equivalent to including class level fixed effects that would subsume heterogeneity at the level of class, teacher, and school.

[16] Other methods of constructing the index of teacher's bias, e.g. principal component analysis, also yield similar findings (results are available on request).

5.2.4 Gender Stereotype versus Caste/Class Stereotype

We consider the fact that the four questions capturing a teacher's subjective beliefs are related to gender, caste, and class. Our analysis so far has considered an aggregate measure of biased or stereotypical beliefs based on these three dimensions. Now we use the index of gender stereotype separately from caste or class related stereotype in the analysis. Results presented in the last two columns of Table 6 show that teacher's gender stereotype has a stronger and statistically significant effect on the gender gap in math learning. Teacher's caste and class related stereotype also has a negative effect, but it is not statistically significant. In all the cases, significant effect is found only due to the male teacher, with the impact of female teachers being statistically not significant.

5.2.5 Additional Interaction Controls

If biased teachers differ in other characteristics than teachers who are not biased, then the effect of biased teachers on gender gap in learning may be confounded with the effect of other teacher characteristics that also have a differential effect by the gender of the student. To address this concern, we include additional interaction of the observable teacher characteristics with the gender of the student in the regression. Moreover, we include interaction of gender of the student with all other student level covariates. This would address the concern that teachers' beliefs are endogenously formed as a gender-differentiated response to students' baseline performance and other characteristics. Column (6) of Table 6 shows that the effect of biased teacher on gender gap in math score is neither explained nor attenuated when we include these additional interaction terms.

5.3 Heterogeneity Analysis

5.3.1 Heterogeneity by Baseline Math Score

We test if the effects vary depending on students' baseline mathematical ability. We divide the students into terciles of their baseline math score and estimate the triple-interaction model (Equation (3)) separately for each of these three categories. The results are presented in Table 7. The effects are significant only for the medium-performing students. The effect of biased teachers on gender gap in math performance is not only significant and negative, but also higher in magnitude than the overall sample: one standard deviation increase in teacher's bias increases the gender gap in math score by 0.12 standard deviation when the teacher is male. However, the triple interaction term is positive and similar in magnitude, albeit not significant. Hence, the effect of biased teachers on gender gap disappears when the teacher is female.

Another interesting result that is found for the medium-performing students is the significant positive effect of teacher's gender on the gender gap in math performance of students. Female teachers, as compared to male teachers, tend to reduce the gender gap in math score by 0.31 standard deviation. This result is consistent with Muralidharan and Sheth (2016), but the magnitude of the effect here is much larger than what they found in their study.

We do not find any significant effect of teacher's bias or gender on students who are either low-performers (first decile) or high-performers (third decile) as defined by their initial mathematical ability. This result indicates that students in the bottom and top end of the ability distribution are less affected by teacher's attitude, while those in the middle of the distribution depend more on teachers for their learning outcomes, and hence they are the ones most affected by teacher's bias.

5.3.2 Heterogeneity by Gender Composition of the Class

In a co-educational class, the gender composition of the peers is likely to influence the learning environment (Schneeweis and Zweimüller, 2012; Eren, 2017). Therefore, considering mixed-gender classes, we test heterogeneity in the effect of biased teachers across two sub-samples – classes with majority of the students being boys (male-dominated class) and majority being girls (female-dominated class). Results presented in Table 8 show that the adverse effect of biased teachers on the gender gap is particularly large and significant in the male-dominated classes. This negative effect of teacher's bias is equally true for both male and female teachers in the male-dominated classes, while the effect is smaller and not significant in female-dominated classes.[17] Thus, our results suggest that girls are especially harmed by biased teachers when they are in a classroom with majority of their peers being boys.

5.4 Mechanism: Student's Attitude towards Math

To explore the potential mechanisms through which biased teachers affect students' math learning, we investigate their effect on students' self-reported attitude towards math. Specifically, we estimate Equation (3) but consider the following three outcomes: math importance, math interest, and math dislike. These measures are constructed as an index based on how students express their view about math on a number of questions which are given in Appendix Table A4. For this analysis, we focus on teacher's bias related to gender. Results presented in Table 9 shows that teachers with stronger stereotypical beliefs make the gender gap in math importance and math dislike significantly worse. Girls, as compared to boys, are more likely to report that they dislike math, and less likely to report that they think math is important, when they are taught by a biased math teacher. The effect on math interest is not statistically significant although it is also negative in sign. As before, we find that the effect of stereotype is driven only by male teachers, while the effect of female teachers is statistically not significant for any of the outcomes. These results indicate that girls feel demotivated to study math when they are taught by a biased teacher, and this may have an impact on their test scores.

5.4.1 Mediation Analysis

We further investigate what proportion of the effect of biased teachers on the gender gap in math score is channeled through students' attitude towards math. In the spirit of causal mediation analysis (Imai et al., 2011; Carpena and Zia, 2020), we decompose the total effect into an indirect effect that is attributable to a specific mediator, and a direct

[17] We get similar findings if instead of subsample analysis, we use interaction term involving the proportion of girls in the class.

effect that represents the remaining pathways. For this exercise, we consider Equation (2) that allows us to estimate the total effect of biased teachers on gender gap in math score (given by the coefficient β_5). For mediation analysis, we additionally estimate the following two equations[18]:

$$\begin{aligned} Mediator_{ijs} = \delta_0 &+ \delta_1 BaselineMath_{ijs} + \delta_2 GirlStudent_{ijs} \\ &+ \delta_3 GirlStudent_{ijs} \times BiasedTeacher_{js} \\ &+ \delta_4 X_{ijs} + \phi_{js} + \psi_s + \varepsilon_{ijs} \end{aligned} \tag{4}$$

$$\begin{aligned} MathScore_{ijs} = \theta_0 &+ \theta_1 BaselineMath_{ijs} + \theta_2 GirlStudent_{ijs} \\ &+ \theta_3 GirlStudent_{ijs} \times BiasedTeacher_{js} + \theta_4 Mediator_{ijs} \\ &+ \theta_5 X_{ijs} + \phi_{js} + \psi_s + \varepsilon_{ijs} \end{aligned} \tag{5}$$

The mediation effect is given by the product of the coefficients $\hat{\delta_3}\hat{\theta_4}$ obtained through ordinary least square (OLS) estimation of the above two equations.[19] The direct effect is captured by the OLS estimate $\hat{\theta_3}$ from Equation (5). The standard error of the mediation effect is obtained through non-parametric bootstrapping.

As a potential mediator, we consider each of the three variables, i.e. math importance, math interest, and math dislike, reflecting a student's attitude towards math. In addition to the overall sample, we also conduct the mediation analysis separately for male and female teachers. Consistent with our earlier findings, results presented in Ta-

[18]Note that we include teacher fixed effects in these equations, hence we deliberately omit terms reflecting teacher specific characteristics such as $FemaleTeacher$, $BiasedTeacher$, or Z from the equations. Our main interest is the interaction term $GirlStudent \times BiasedTeacher$ that allows us to estimate the effect of biased teacher on the gender gap in outcome.

[19]Imai et al. (2011) points out that the assumption of "sequential ignorability" is required in order to have a causal interpretation of the mediation effect estimated here. This assumption implies that (a) there is no omitted variable bias in identifying δ_3 from Equation (4), and (b) the mediator variable included in Equation (5) is exogenous conditional on the other explanatory variables included in that equation. Part (b) of this assumption is fairly strong and may not hold, for instance, if students' attitude towards math and performance in the math test are simultaneously determined. Moreover, identification of the mediation effect in the above models also assumes linearity and no interaction between the mediator and the main treatment variable; however our results are unchanged even if we include an interaction term involving the mediator in Equation (5).

ble 10 show that math importance and math dislike significantly mediates the effect of biased teachers on the gender gap in math score. Despite being statistically significant, the effect of these mediators is rather small in magnitude as compared to the direct effect. Only 4 percent of the total effect is channeled through students' perceptions about math being an important subject. This proportion is about 10 percent when we consider students' dislike for math as a mechanism. The lower two panels of Table 10 show that these effects are entirely driven by the male teachers.

5.5 Language (English) Score

We estimate the same models with a different learning outcome: English score. Appendix Table A5 shows that the results are different than what we found in the context of math outcome. While we do find a negative and significant effect of biased teachers on English score, there is no differential effect on gender gap; moreover, the coefficients are statistically not significant once we include teacher fixed effects. We also find a significant positive effect of female teachers on English score of students, but the effect may not be robust to teacher specific unobserved characteristics. The finding that biased teachers are especially harmful for mathematics performance of girls, but not necessarily for English performance, is consistent with Carlana (2019) who finds similar evidence from Italy.

6 Conclusion

This study evaluates the effect of teacher's stereotype on student's learning outcomes in the Indian context. There is a growing body of literature that seeks to identify the effect of teacher's identity, such as gender, race, etc., on students' learning outcomes. Some of these studies have found female teachers to have positive effect on girls' math performance. On the other hand, another set of studies indicates that biased teachers have a negative effect on girls' math scores. Our findings connect to both these types of studies by showing that the negative effect of biased teachers also depends on the gender of the teacher: the gender gap in math performance widens when students are taught by a biased teacher who is male. In contrast, biased female teachers do not have any significant effect on math score. Moreover, considering students who are medium-performers, female teachers tend to improve girls' math performance and thus reduce the gender gap. We also show that biased teachers negatively affect girls' attitude towards math learning as compared to boys. Furthermore, we find that these effects are significant only for math outcome, as no such effect is found on English score. This is also consistent with the literature which shows a significant gender gap in math performance among adolescent students in various parts of the world, while girls are at par with (or better than in some instances) boys in literature.

Our study highlights the need for recognizing the role of teachers' influence on the gender gap in students' performance in mathematics, which has further implications in terms of the choice of streams and future earnings of girls. In societies where inequality is pervasive and manifests itself in various forms, stereotypes against girls and disadvantaged groups may creep into the classroom via teachers. This hampers the learning process and reproduces the inequalities that education is supposed to reduce. One potential policy measure is to include gender-sensitization as a part of in-service teacher training. Whether such a policy would be effective is a future research question. However, there seems to be some merit in encouraging hiring of women as teachers because they have beneficial effects on girls, which off-sets any negative effect resulting from stereotypical attitudes held by teachers.

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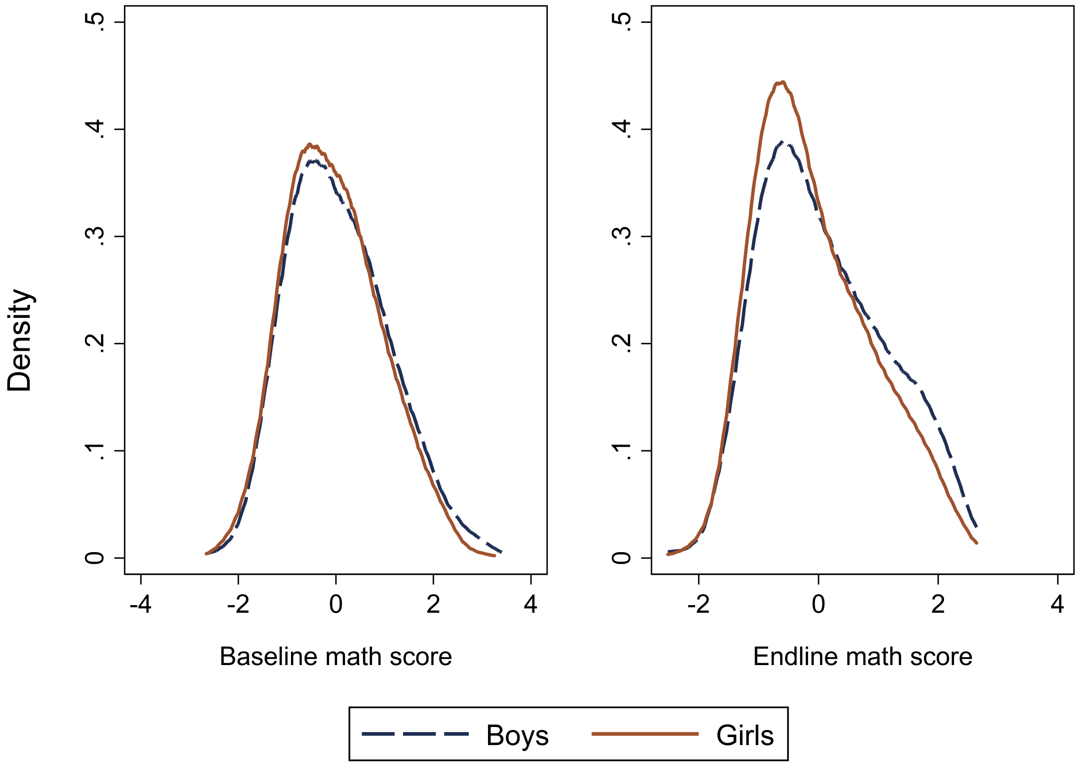
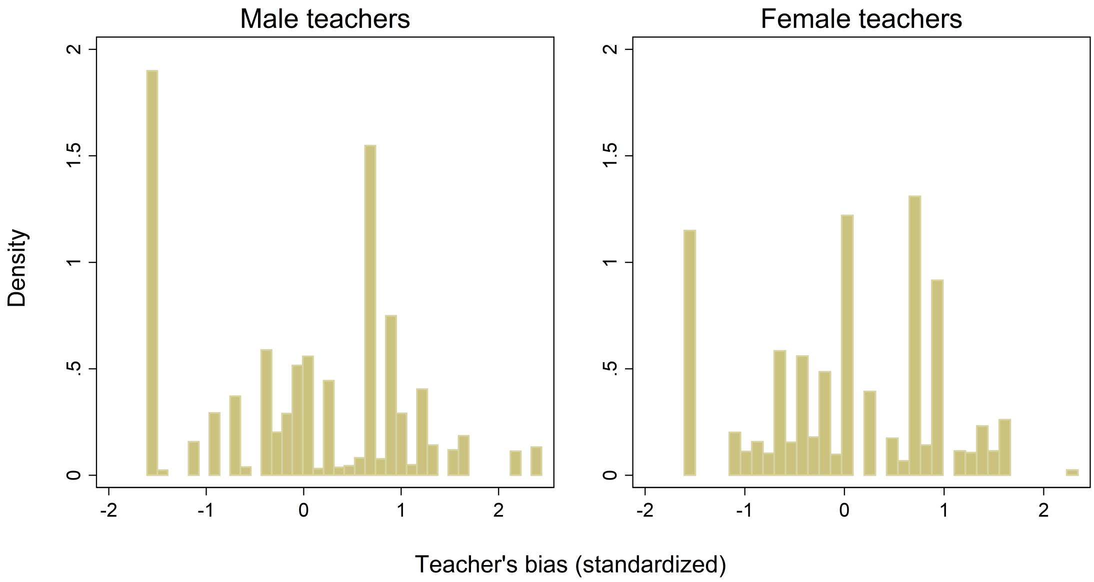
Figure 1: Distribution of math scores by gender of student



Notes: Standardized math scores are plotted by gender. The left panel shows the distribution at the beginning of the academic year, and the right panel shows the distribution at the end of the academic year for the ninth grade students included in the Young Lives school survey 2016-17.

Figure 2: Distribution of math teacher's bias by teacher's gender



Notes: Histogram for the index of teacher's bias is shown by teacher's gender. Only math teachers are considered. The index is derived out of the teacher's subjective beliefs about the role of gender, class, and caste in students' learning outcomes; these components of the index are shown in Table 1.

Table 1: Distribution of math teachers' responses to questions related to bias

	Strongly disagree	Disagree	Agree	Strongly agree
Gender can predict how well the student will fare.	53.32	43.48	2.97	0.23
Boys are able to do better in studies than girls.	30.45	59.97	8.37	1.22
A child's caste background affects how well they can learn.	29.2	45.01	24.92	0.87
Children from poor backgrounds are less capable of learning.	42.11	46.69	9.79	1.41

Note: Each cell denotes the row percentage and the row total adds up to 100

Table 2: Summary statistics of student related variables

Variable	Mean	SD
Math Rawscore Wave 2	19.627	7.781
Math Rawscore Wave 1	17.815	6.563
Girl	0.595	0.491
Age	14.034	0.716
Lower caste	0.850	0.357
Urban locality	0.390	0.488
Mother is alive	0.978	0.146
Father is alive	0.931	0.254
Whether mother can read		
She can read and write well	0.255	0.436
She can read and write a little	0.326	0.469
Not known	0.034	0.181
Mother's education		
Primary School (Class I-V)	0.234	0.423
Upper Primary School (Class VI-VII)	0.105	0.307
High School (Class VIII-X)	0.165	0.371
Junior College (Class XI-XII)	0.055	0.229
Higher education (e.g. University, Diploma)	0.046	0.209
Not known	0.077	0.266
Whether father can read		
He can read and write well	0.412	0.492
He can read and write a little	0.285	0.452
Not known	0.053	0.223
Father's education		
Primary School (Class I-V)	0.195	0.396
Upper Primary School (Class VI-VII)	0.105	0.307
High School (Class VIII-X)	0.196	0.397
Junior College (Class XI-XII)	0.098	0.298
Higher education (e.g. University, Diploma)	0.099	0.299
Not known	0.098	0.297

The number of observations used to calculate the summary statistics for the above student related variables is 7682.

Table 3: Summary statistics of math teacher related variables

Variable	Mean	SD
Math teacher's bias	-.026	.983
Female math teacher	.327	.470
Math teacher is lower caste	.641	.480
Math teacher's age	38.604	10.655
Math teacher is head teacher	.0519	.222
Math teacher can use English for conversations	.773	.420
Math teacher's education		
Bachelor's degree	0.365	0.481
Postgraduate degree	0.608	0.488
MPhil	0.009	0.095
Math teacher's teacher training qualification		
D.Ed / TTC / other Diploma	0.013	0.112
B.Ed	0.854	0.353
M.Ed	0.102	0.302
Other	0.009	0.092
Math teacher is temporary/fixed term	0.327	0.469
Math teacher does extra work apart from school	0.044	0.206

The number of observations on teachers included in the sample is 272.

Table 4: Effect of having a biased math teacher on students' math score.

	Outcome: Math score		
	(1)	(2)	(3)
Baseline math score	0.552***	0.551***	0.463***
	(0.011)	(0.011)	(0.016)
Girl student	-0.060***	-0.063***	-0.025
	(0.020)	(0.020)	(0.032)
Biased teacher	-0.014	0.011	
	(0.009)	(0.013)	
Female teacher	-0.072***	-0.075***	
	(0.022)	(0.022)	
Girl student × Biased teacher		-0.046***	-0.068**
		(0.018)	(0.030)
Constant	0.188	0.160	0.374**
	(0.223)	(0.223)	(0.185)
Observations	6,964	6,964	7,682
R-squared	0.473	0.473	0.614
Other control variables	Yes	Yes	Yes
School fixed effects	No	No	Yes
Teacher fixed effects	No	No	Yes

Other control variables include student characteristics and teacher characteristics. Student characteristics are student's age, caste, whether mother is alive, whether father is alive, whether mother can read, whether father can read, mother's education level, father's education level, whether resides in a rural locality, and district dummies. Teacher characteristics are teacher's caste, age, whether teacher is a head teacher, if teacher is able to converse in English, their highest level of education (excluding teacher training), their highest level of teacher training qualification, the nature of contract (permanent versus temporary), and whether they do any extra work apart from their work at this school to supplement their income. As we are using teacher fixed effects in (3), we do not include teacher characteristics in that regression. Robust standard errors in parentheses. Standard errors are further clustered at the teacher level in column 3. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of biased teacher by teacher's gender.

	Outcome: Math score		
	Math teacher		
	All	Male	Female
	(1)	(2)	(3)
Baseline math score	0.463***	0.487***	0.412***
	(0.016)	(0.020)	(0.022)
Girl student	-0.029	-0.029	-0.006
	(0.036)	(0.036)	(0.076)
Girl student × Biased teacher	-0.069**	-0.068**	-0.064
	(0.032)	(0.032)	(0.074)
Girl student × Female teacher	0.023		
	(0.083)		
Girl student × Biased teacher × Female teacher	0.007		
	(0.078)		
Constant	0.369*	0.537**	0.088
	(0.187)	(0.226)	(0.319)
Observations	7,682	4,934	2,748
R-squared	0.614	0.617	0.586
Other control variables	Yes	Yes	Yes
School fixed effects	Yes	Yes	Yes
Teacher fixed effects	Yes	Yes	Yes

Other control variables are according to what has been mentioned in Table 4. As we are using teacher fixed effects in all the models above, we do not include teacher characteristics. Robust standard errors clustered at the teacher level are in parentheses. The double interaction between biased teacher and female teacher do not appear because it is absorbed by teacher fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Robustness of results to alternative samples, measures of teacher's bias, and specifications

	Outcome: Math score					
	(1) Attrition corrected	(2) Mixed class	(3) Alternative measure	(4) Gender stereotype	(5) Caste/class stereotype	(6) Interaction controls
Baseline math score	0.463***	0.482***	0.463***	0.463***	0.463***	0.448***
	(0.016)	(0.021)	(0.016)	(0.016)	(0.016)	(0.016)
Girl student	-0.028	-0.034	-0.030	-0.027	-0.027	-0.251
	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)	(0.512)
Girl student × Biased teacher	-0.069**	-0.066**	-0.071**	-0.073**	-0.044	-0.087**
	(0.033)	(0.033)	(0.033)	(0.034)	(0.037)	(0.039)
Girl student × Female teacher	0.021	0.024	0.029	0.035	0.015	0.074
	(0.083)	(0.096)	(0.083)	(0.084)	(0.079)	(0.100)
Girl student × Biased teacher × Female teacher	0.009	-0.007	0.029	0.062	-0.054	0.043
	(0.078)	(0.085)	(0.079)	(0.082)	(0.086)	(0.096)
Constant	0.360*	0.513**	0.368*	0.368*	0.378**	0.199
	(0.190)	(0.236)	(0.187)	(0.188)	(0.186)	(0.284)
Effect of biased female teacher	-0.059	-0.073	-0.043	-0.011	-0.098	-0.044
	(0.070)	(0.079)	(0.072)	(0.074)	(0.077)	(0.089)
Observations	7,682	4,362	7,682	7,682	7,682	6,964
R-squared	0.612	0.613	0.614	0.614	0.614	0.606
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
School fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Teacher fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Other control variables are according to what has been mentioned in Table 4. As we are using teacher fixed effects in all the models above, we do not include teacher characteristics. Attrition in test scores measured in wave 2 is corrected using an inverse probability weighting method in column 1. Column 2 presents regression on sample of students who study in a mixed-sex classroom. The measure in Column 1 follows Alan et al. (2018). Column 4 considers teacher's bias measured only on questions related to gender. Column 5 considers a measure of teacher's bias based on questions unrelated to gender, but related to caste and class. Column 6 has additional control variables that interact *Girl student* with all student and teacher level covariates. Robust standard errors clustered at the teacher level are in parentheses. The double interaction between biased teacher and female teacher do not appear because it is absorbed by teacher fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Heterogeneity of effects depending on baseline performance of students.

	Outcome: Math score		
	Baseline Math performance:		
	Low	Medium	High
	(1)	(2)	(3)
Baseline math score	0.261***	0.462***	0.531***
	(0.030)	(0.052)	(0.033)
Girl student	0.038	-0.086	-0.011
	(0.059)	(0.054)	(0.051)
Girl student × Biased teacher	-0.024	-0.119**	-0.059
	(0.056)	(0.047)	(0.048)
Girl student × Female teacher	-0.138	0.314**	-0.066
	(0.117)	(0.144)	(0.094)
Girl student × Biased teacher × Female teacher	0.060	0.102	-0.034
	(0.100)	(0.117)	(0.111)
Constant	-0.080	-0.039	0.877*
	(0.281)	(0.359)	(0.481)
Effect of biased female teacher	0.036	-0.017	-0.093
	(0.085)	(0.107)	(0.100)
Observations	2,622	2,504	2,486
R-squared	0.398	0.429	0.521
Other control variables	Yes	Yes	Yes
School fixed effects	Yes	Yes	Yes
Teacher fixed effects	Yes	Yes	Yes

Other control variables are according to what has been mentioned in Table 4. As we are using teacher fixed effects in all the models above, we do not include teacher characteristics. Robust standard errors clustered at the teacher level are in parentheses. The double interaction between biased teacher and female teacher do not appear because it is absorbed by teacher fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Heterogeneity of effects depending on proportion of girl students in mixed classrooms.

	Outcome: Math score	
	Proportion of girls:	
	Less than 50%	More than 50%
	(1)	(2)
Baseline math score	0.502***	0.441***
	(0.029)	(0.028)
Girl student	-0.031	-0.043
	(0.050)	(0.049)
Girl student × Biased teacher	-0.104**	-0.038
	(0.045)	(0.043)
Girl student × Female teacher	0.201	-0.100
	(0.136)	(0.111)
Girl student × Biased teacher × Female teacher	-0.033	-0.075
	(0.083)	(0.111)
Constant	0.621*	0.211
	(0.339)	(0.361)
Effect of biased female teacher	-0.137*	-0.112
	(0.072)	(0.102)
Observations	2,289	2,472
R-squared	0.604	0.632
Other control variables	Yes	Yes
School fixed effects	Yes	Yes
Teacher fixed effects	Yes	Yes

Other control variables are according to what has been mentioned in Table 4. As we are using teacher fixed effects in all the models above, we do not include teacher characteristics. Robust standard errors in parentheses. The double interaction between biased teacher and female teacher do not appear because it is absorbed by teacher fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Effect of biased math teachers on students' attitude towards math

	Outcome: Math importance (1)	Math interest (2)	Math dislike (3)
Baseline math score	0.078***	0.138***	-0.254***
	(0.015)	(0.015)	(0.017)
Girl student	0.046	0.015	-0.072*
	(0.040)	(0.042)	(0.039)
Girl student × Biased teacher	-0.058*	-0.020	0.083*
	(0.034)	(0.039)	(0.044)
Girl student × Female teacher	-0.069	0.010	-0.030
	(0.078)	(0.095)	(0.078)
Girl student × Biased teacher × Female teacher	0.060	-0.034	-0.112
	(0.072)	(0.090)	(0.085)
Constant	0.644***	0.569**	-0.427
	(0.243)	(0.224)	(0.278)
Effect of biased female teacher	0.001	-0.054	-0.029
	(0.064)	(0.081)	(0.074)
Observations	9,160	9,160	9,160
R-squared	0.127	0.150	0.145
Other control variables	Yes	Yes	Yes
School fixed effects	Yes	Yes	Yes
Teacher fixed effects	Yes	Yes	Yes

Other control variables are according to what has been mentioned in Table 4. As we are using teacher fixed effects in all the models above, we do not include teacher characteristics. Robust standard errors clustered at the teacher level are in parentheses. The double interaction between biased teacher and female teacher do not appear because it is absorbed by teacher fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Mediation analysis exploring channels through which biased teachers affect gender gap in math score

	Mediator:		
	Math importance	Math interest	Math dislike
	(1)	(2)	(3)
Overall			
Mediation effect	-0.003*	-0.002	-0.006*
	(0.002)	(0.002)	(0.004)
Direct effect	-0.058*	-0.059*	-0.055*
	(0.031)	(0.031)	(0.031)
Total effect	-0.061*	-0.061*	-0.061*
	(0.032)	(0.032)	(0.032)
Percent mediated	4.21	3.63	9.84
Observations	7,682	7,682	7,682
Male teachers			
Mediation effect	-0.003*	-0.001	-0.008**
	(0.002)	(0.002)	(0.004)
Direct effect	-0.069**	-0.071**	-0.065*
	(0.033)	(0.033)	(0.033)
Total effect	-0.073**	-0.073**	-0.073**
	(0.034)	(0.034)	(0.034)
Percent mediated	4.28	1.87	10.43
Observations	4,934	4,934	4,934
Female teachers			
Mediation effect	0.000	-0.005	-0.001
	(0.004)	(0.004)	(0.009)
Direct effect	-0.014	-0.009	-0.013
	(0.074)	(0.074)	(0.071)
Total effect	-0.014	-0.014	-0.014
	(0.077)	(0.077)	(0.077)
Percent mediated	-0.01	34.73	7.09
Observations	2,748	2,748	2,748

Total effect captures the effect of biased teachers (gender-stereotype) on the gender gap in math score. Total effect is decomposed into mediation effect (explained by a specific mediator) and direct effect (not explained by the mediator). We consider three mediator variables capturing students' attitude towards math, as indicated in the column heading. All models include control variables same as in column (3) of Table 4, including teacher fixed effects. Robust standard errors clustered at the teacher level are in parentheses. Standard errors of mediation effects are bootstrapped. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A1: Correlates of math teacher's bias.

	(1)	(2)
Female teacher	0.147	0.147
	(0.140)	(0.141)
Teacher lower caste	0.086	0.135
	(0.137)	(0.145)
Age	0.005	0.006
	(0.008)	(0.007)
Years of experience	0.011	0.009
	(0.009)	(0.008)
Salary less than equal to 40,000	-0.281	-0.287
	(0.198)	(0.196)
Math teacher is head teacher	0.010	-0.016
	(0.300)	(0.290)
Can use English for conversation	-0.332**	-0.289*
	(0.156)	(0.155)
Asset index	-0.105***	-0.100***
	(0.035)	(0.036)
Masters degree or above	0.088	0.109
	(0.135)	(0.136)
B.Ed or M.Ed	-0.063	-0.030
	(0.231)	(0.233)
Permanent position	-0.344*	-0.323*
	(0.193)	(0.195)
Fulltime teacher	-0.402	-0.439*
	(0.247)	(0.234)
State government school	-0.283*	-0.339**
	(0.147)	(0.152)
Constant	0.621	0.564
	(0.446)	(0.424)
Observations	248	248
R-squared	0.116	0.150
District fixed effects	No	Yes

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A2: Assignment of biased math teachers

	Biased teacher								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Baseline math score	-0.098	-0.210	-0.160	-0.272	-0.192				
	(0.093)	(0.211)	(0.259)	(0.502)	(0.778)				
Proportion of girl students	0.019	0.083	-0.003	0.490	1.434	0.185	0.192	1.303	0.428
	(0.190)	(0.211)	(0.262)	(0.878)	(1.959)	(0.404)	(0.494)	(1.631)	(3.585)
Baseline Math score × Proportion of girls		0.217	0.103	0.121	0.136				
		(0.346)	(0.403)	(0.768)	(1.014)				
Average baseline test scores of girls						-0.036	-0.059	-0.058	0.872
						(0.161)	(0.173)	(0.471)	(0.892)
Average baseline test scores of boys						-0.009	0.100	0.247	-0.589
						(0.148)	(0.175)	(0.418)	(0.723)
Constant	-0.028	-0.059	3.385	16.151	5.682	-0.173	5.596	35.190**	21.975
	(0.127)	(0.136)	(4.015)	(11.491)	(20.586)	(0.225)	(4.650)	(12.846)	(25.800)
Observations	272	272	271	123	102	194	193	88	73
R-squared	0.005	0.006	0.097	0.709	0.891	0.002	0.152	0.794	0.970
Student characteristics	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes
District fixed effects	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes
School fixed effects	No	No	No	Yes	Yes	No	No	Yes	Yes
Teacher characteristics	No	No	No	No	Yes	No	No	No	Yes

Student and teacher characteristics are according to what has been mentioned in Table 4. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Assignment of female math teachers

	Female teacher								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Baseline math score	-0.087**	-0.074	-0.128	-0.141	0.120				
	(0.036)	(0.071)	(0.097)	(0.272)	(0.358)				
Proportion of girl students	0.710***	0.703***	0.675***	0.321	0.135	0.331*	0.336	0.133	1.761
	(0.087)	(0.095)	(0.121)	(0.367)	(0.679)	(0.175)	(0.217)	(0.931)	(1.067)
Baseline Math score × Proportion of girls		-0.024	-0.007	0.170	-0.218				
		(0.137)	(0.163)	(0.287)	(0.364)				
Average baseline test scores of girls						0.089	0.075	0.131	0.600*
						(0.057)	(0.063)	(0.238)	(0.258)
Average baseline test scores of boys						-0.111**	-0.185***	-0.306	-0.554
						(0.056)	(0.065)	(0.294)	(0.286)
Constant	-0.066	-0.063	0.569	-4.313	-1.564	0.047	-0.400	-3.625	0.741
	(0.054)	(0.055)	(1.635)	(5.425)	(8.884)	(0.091)	(1.853)	(7.125)	(8.688)
Observations	263	263	263	113	102	187	187	80	73
R-squared	0.238	0.238	0.313	0.849	0.942	0.046	0.284	0.796	0.975
Student characteristics	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes
District fixed effects	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes
School fixed effects	No	No	No	Yes	Yes	No	No	Yes	Yes
Teacher characteristics	No	No	No	No	Yes	No	No	No	Yes

Student and teacher characteristics are according to what has been mentioned in Table 4. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Students' math attitude.

	Strongly disagree	Disagree	Agree	Strongly agree
Math importance				
The things I learn in maths will be important to me in the future	2.25	2.85	46.27	48.63
Maths is important to me personally	2.19	4.58	49.04	44.18
Math interest				
I look forward to my maths lessons	3.83	10.46	57.07	28.64
I am interested in the things I learn in maths	2.55	7.51	53.3	36.64
When I do maths, I sometimes get totally absorbed	2.63	10.18	56.39	30.8
Because doing maths is fun, I wouldn't want to give it up	4.49	11.09	51.23	33.19
Studying maths gives me a lot of personal satisfaction	3.19	7.97	55.43	33.42
I do extra work in maths topics that I like	3.48	9.04	50.08	37.4
Math dislike				
I find maths really boring	27.71	42.1	20.16	10.03
I would rather spend my time on subjects other than Maths	8.74	34.17	39.58	17.5
Learning maths is a waste of time	36.75	38.67	15.57	9.01

Note: Each cell denotes the row percentage and the row total adds up to 100.

Table A5: Effect of biased English teachers on English score

	Outcome: English score			
	(1)	(2)	(3)	(4)
Baseline English score	0.630***	0.630***	0.478***	0.477***
	(0.010)	(0.010)	(0.020)	(0.020)
Girl student	-0.034**	-0.034**	0.015	-0.011
	(0.016)	(0.016)	(0.026)	(0.029)
Biased teacher	-0.027***	-0.017		
	(0.008)	(0.013)		
Female teacher	0.069***	0.070***		
	(0.017)	(0.017)		
Girl student × Biased teacher		-0.019	0.006	0.023
		(0.016)	(0.026)	(0.026)
Girl student × Female teacher				0.061
				(0.054)
Girl student × Biased teacher × Female teacher				-0.035
				(0.057)
Constant	0.143	0.135	0.280*	0.272*
	(0.197)	(0.197)	(0.154)	(0.155)
Effect of biased female teacher				-0.012
				(0.050)
Observations	7,086	7,086	7,598	7,598
R-squared	0.663	0.664	0.749	0.749
Other control variables	Yes	Yes	Yes	Yes
School fixed effects	No	No	Yes	Yes
Teacher fixed effects	No	No	Yes	Yes

Other control variables are according to what has been mentioned in Table 4. As we are using teacher fixed effects in (3) and (4) above, we do not include teacher characteristics. Robust standard errors in parentheses. Standard errors are further clustered at the teacher level in columns 3 and 4. *** p<0.01, ** p<0.05, * p<0.1