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A teacher like me or a student like me? Role model versus teacher bias effect

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ABSTRACT

Several studies have found that teacher–student gender matching has positive effects on student achievement. However, the underlying mechanisms that explain this effect have not been empirically explored. This paper studies the impact of same gender teachers on academic achievement for a large sample of 8th graders in Chile. I provide evidence that girls benefit from being assigned to female teachers, while there is no negative effect on boys. More importantly, I provide evidence that the positive effect is due to role model effects and not to teacher bias effects.

1. Introduction

Numerous studies have documented a gap in the average educational achievement between boys and girls. This gap is especially important in math and language, with boys outperforming girls in math and girls outperforming boys in language. In Chile in 2009, the gender gap in a standardized test taken by 8th grade students was 0.19 standard deviations in math and −0.23 standard deviations in language.[1] This gap is also present in developed countries such as the United States, Australia and England (Mead, 2006). In the United States, using the 1999 NAEP Scores for 13 year old students, the gender gap was 0.083 standard deviations in math and −0.305 standard deviations in reading (Dee, 2007). Fryer and Levitt (2010) document a gender gap in math in the United States across every stratum of society.

It is important to understand the factors determining this gap, because it may drive gender differences in the labor market. For example, women in Chile tend to study fields leading to careers in education and health, whereas men tend to study fields leading to careers in science and math, which on average are associated with higher wages. This may have implications for women's returns to schooling and may relate to occupational segregation and earnings inequality by gender (Loury, 1997).

One explanation that has been discussed in the literature emphasizes the gender of language and math teachers. First, the gender of the teacher can have an effect on students' behavior through role model effects or through stereotype threats (see Dee, 2007). If we think of teachers as role models, and if students identify themselves more with same-sex role models, then it is possible that performance will be enhanced when students are assigned to a same gender teacher.[2] The same result is

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[1] These numbers were calculated as the male mean test score minus the female mean test score using data from the Measuring the Quality of Education test.

[2] As discussed in Basow and Howe (1980), "Because part of role modelship is identification, both sexes should be more influenced by same rather than other sex models."

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also consistent with the theory of stereotype threats, which states that, in the case of negative stereotypes against a group, group members may internalize the stereotypes as explanations of their own behavior (see Holmlund & Sund, 2008). In both cases, it is the student who is reacting to the gender of the teacher.

Second, the teacher gender may matter because of teachers' behavior. For example, teachers might have a preference toward students of their own sex, and hence female (male) teachers will structure their classrooms in ways that enhance girls' (boys') learning. If not preferences, gender stereotypes about students may influence teachers' behavior. In both cases, it is the teacher reacting to the gender of the student.

Several studies have found that teacher–student gender matching has positive effects. At the college level, Bettinger and Long (2005) show that the presence of faculty members of the same gender has a positive and significant impact on course selection and on choice of major. Hoffmann and Oreopoulos (2009) find that teacher gender plays little or no role in student achievement and choice of field. The effect appears driven more by males performing worse when assigned to a female teacher, with no effect for females. Carrell, Page, and West (2010) find a limited impact of teacher gender on male students' achievement, while it has a powerful effect on female students' outcomes.At the high school level, Nixon and Robinson (1999) estimate the effect of the percentage of high school female faculty on female years of schooling, high school graduation, enrollment in college and graduation from college. They find a positive effect of female faculty on female students, with no effect on male students. Holmlund and Sund (2008) use a large dataset of secondary students in Sweden and find no effect. Ehrenberg, Goldhaber, and Brewer (1995) also find no effect on students' test scores, but a positive effect on teachers' subjective evaluations.

At the middle school level, Dee (2007) finds that assigning an opposite gender teacher lowers student achievement, as well as affecting teacher perceptions of student behavior, with teacher perceptions more negative for opposite gender students. Ammermueller and Dolton (2006), using the same methodology as Dee (2007), find positive gender interactions for England but not for the United States. Cho (2012) uses data from the Trends in International Mathematics and Science Study to investigate the impact of teacher–student gender matching in 15 OECD countries. The results show that teacher's gender has no impact on student test scores in eight countries, has a positive impact on boys' test scores in four countries, and has a positive impact on girls' test scores in the remaining three countries. Moreover, the positive impact can be explained by differences in teacher quality.

Few studies explore the mechanisms through which the gender of the teacher impacts student achievement. Nixon and Robinson (1999) argue that, because the effect of a female teacher on boys is negative or zero, they can rule out explanations such as female faculty being better teachers or schools with a higher proportion of female faculty being better schools. Carrell et al. (2010) distinguish the effect of professor gender itself from the role of other professor characteristics that are correlated with gender. To do this, they estimate each professor's average value added separately for men and women, and they include the estimated value added as a control variable. However, these studies cannot rule out teacher bias effect. Hoffmann and Oreopoulos (2009) argue that, because they focus on large undergraduate classes where teachers do not grade students' exams and students do not typically receive differential treatment from teachers, they can attribute the effect to role model effects and not to teacher bias effects.

In this study, I investigate the effect of the teacher gender on the educational achievement of boys and girls for the case of Chile. My study contributes to the literature in several ways. First, I use the matched pairs approach suggested by Dee (2007) to control for individual unobserved characteristics, but I also control for students' subject specific propensity for achievement, which could have biased previous studies. Second, and more importantly, I present a theoretical framework that provides some clear empirical predictions that can be tested with the data to determine whether the positive effect is due to teacher bias effect or role model effect. I provide evidence that suggests that the gender interaction effect can be attributed to a role model effect and not a teacher bias effect.

Section 2 develops a theoretical framework to understand the mechanisms through which gender matching could have a positive effect. Sections 3 and 4 introduce the data and the econometric framework used in this study. In Section 5, the main results are analyzed and the internal validity of the estimates is discussed. Section 6 presents evidence regarding the possible mechanisms, and Section 7 concludes.

2. Theoretical framework

As discussed in Section 1, student–teacher gender matching can be beneficial for students for different reasons. This section develops a model of student learning and teacher time allocation, which allows learning to be affected by role models, and allows teachers to have a preference toward their own gender. I first show that there could exist a positive effect of gender matching due to role model effects and/or teacher bias effects. Second, to distinguish between role model effects and teacher bias, I explore the different predictions from these two theories.

2.1. Teacher decision

Suppose the teacher has a fixed number of hours to allocate to teaching and can divide them into hours of teaching devoted to boys, h_1, and hours of teaching devoted to girls, h_2. The teacher can have a preference toward his or her own gender, which is captured by $\alpha_t \leq 1$, where $t \in \{1,2\}$ for male and female teachers, respectively. The maximization problem for the teacher is the following:

$$\text{Max}_{h_{1t},h_{2t}} V_t = \sum_{i=1}^{2} \alpha_{it} \frac{N_i}{N_1 + N_2} U(h_{it}) \quad \text{s.t.}\ \bar{h} = h_{1t} + h_{2t} \qquad (1)$$

where U is an increasing function and

$$\alpha_{it} = \begin{cases} 1 & \text{if } i = t \\ \alpha_t \leq 1 & \text{otherwise} \end{cases}$$

If teachers have a preference toward their own gender, then $\alpha_t < 1$. When this is the case, female teachers allocate more time to girls (and less to boys) than do male teachers. More formally, if $\alpha_t < 1$, then $h_{ii} > h_{ij}$, with $i \neq j$ and $i,j \in \{1,2\}$.[3] If there is no teacher bias, there should be no difference in time allocation between male and female teachers, such that $h_{ii} > h_{ij}$.[4]

2.2. Student learning

Suppose students' standardized scores are produced through the following learning function:

$$S_{it} = l(f_i(h_{it}, h_{jt}), \beta_i r_{iths}, ability_i) + \varepsilon \quad (2)$$

where $i \neq j$ and $i, j \in \{1, 2\}$, r is the role model effect and ε is a random shock. $f_i(h_{it}, h_{jt}) = (h_{it}/N_i) + \gamma_i(h_{jt}/N_i + N_j)$ so $\gamma_i < 1$ captures the idea that boys and girls can learn from hours dedicated to the opposite gender, h_{jt}, but learn more from hours dedicated to their own gender, h_{it}. The role model effect depends on the teacher (t), the student's household (h) and the society (s) in the following way:

$$r_{iths} = g(r_{it}, r_{ih}, r_{is}) \quad (3)$$

where g is an increasing function in all its components, r_{it} is equal to 1 if the teacher is of the same gender as the student and 0 if not, and $\partial^2 g/\partial r_{it}\partial r_{ih} < 0$ and $\partial^2 g/\partial r_{it}\partial r_{is} < 0$. These last two derivatives capture the idea that the role model effect of the teacher is greater for students who do not have other strong role models in their household, and for subjects for which society has negative expectations about their gender's ability. If $\beta_i > 0$, then students who are exposed to positive role models have higher test scores. If $\beta_i = 0$, there is no role model effect.

2.3. Exploring the possible mechanisms

The model captures the idea that the gender of the teacher can affect students' test scores through a role model effect or through a teacher bias effect. First, let us assume there is only a teacher bias effect, i.e., $\alpha_t < 1$ and $\beta_i = 0$. Then, teachers allocate more time to students that share their gender than do opposite gender teachers, so the expected effect of gender matching on students' test scores is the following:

$$E[S_{ii} - S_{ij}] = l(f_i(h_{ii}, h_{ji}), 0, ability_i) - l(f_i(h_{ij}, h_{jj}), 0, ability_i) > 0$$

This effect is positive because $h_{ii} > h_{ij}$ and

$$f_i(h_{ii}, h_{ji}) = \frac{h_{ii}}{N_i} + \gamma_i \frac{\bar{h} - h_{ii}}{N_1 + N_2} > f_i(h_{ij}, h_{jj}) = \frac{h_{ij}}{N_i} + \gamma_i \frac{\bar{h} - h_{ij}}{N_1 + N_2}.$$

If $\alpha_t = 1$ and $\beta_i > 0$, the amount of hours dedicated to students of gender i is the same for male and female teachers, $h_{ii} = h_{ij}$, but the role model effect is larger for same gender teachers, and so the expected effect of being assigned to a same gender teacher teacher on students' test scores is the following:

$$E[S_{ii} - S_{ij}] = l(f_i(h_{ii}, h_{ji}), \beta_i r_{iihs}, ability_i) - l(f_i(h_{ij}, h_{jj}), \beta_i r_{ijhs}, ability_i) > 0$$

This effect is positive because $r_{iihs} = g(1, r_{ih}, r_{is}) > r_{ijhs} = g(0, r_{ih}, r_{is})$.

This simple model shows that a positive effect of teacher–student gender matching can be explained by a role model effect ($\beta_i > 0$) or a teacher bias effect ($\alpha_t < 1$). To distinguish between these two mechanisms, we need to study the effect for different levels of parental education, for different subjects and for mixed versus gender segregated classrooms.

We can compare the effect of teacher gender for students with different levels of parental education. Mother's education will increase r_{2h}, so a girl whose mother has more education will have a higher r. On the other hand, father's education will increase r_{1h}. The difference of the teacher effect for different levels of parental education is the following:

$$E[S_{ii} - S_{ij}|high] - E[S_{ii} - S_{ij}|low] = l(f_i(h_{ii}, h_{ji}), \beta_i r_{ii,high,s}) - l(f_i(h_{ij}, h_{jj}), \beta_i r_{ij,high,s}) - l(f_i(h_{ii}, h_{ji}), \beta_i r_{ii,low,s}) + l(f_i(h_{ij}, h_{jj}), \beta_i r_{ij,low,s})$$

Because $(\partial^2 g/\partial r_{it}\partial r_{ih}) < 0$, then $r_{ii,high,s} - r_{ij,high,s} < r_{ii,low,s} - r_{ij,low,s}$. If $\beta_i > 0$ the expression is negative, which means that the effect of having a female (male) teacher is larger for girls (boys) whose mothers (fathers) have lower levels of education. If $\beta_i = 0$, the effect of teacher–student gender matching does not depend on parental education.

A critical assumption for this result is that α_t does not vary by parental education. For example, if biased teachers are selected to teach classes with lower levels of parental education, then the effect of a female (male) teacher is larger for girls (boys) whose mothers (fathers) have lower levels of education, even if $\beta_i = 0$.

We can also compare the effect of the teacher gender for different subjects. For girls, r_{2s} will be lower for subjects that are traditionally male dominated than for subjects that are traditionally female dominated (the opposite is true for boys). Then, the difference in the teacher effect for a subject that society *favors* for the student's gender minus a subject that society is biased *against* for the student's gender is the following:

$$E[S_{ii} - S_{ij}|favor] - E[S_{ii} - S_{ij}|against] = l(f_i(h_{ii}, h_{ji}), \beta_i r_{iih,favors}) - l(f_i(h_{ij}, h_{jj}), \beta_i r_{ijh,favors}) - l(f_i(h_{ii}, h_{ji}), \beta_i r_{iih,against}) + l(f_i(h_{ij}, h_{jj}), \beta_i r_{ijh,against})$$

Because $(\partial^2 g/\partial r_{it}\partial r_{is}) < 0$, then $r_{iih,favors} - r_{ijh,favors} < r_{iih,against} - r_{ijh,against}$. If $\beta_i > 0$ the expression is negative, which means that the effect of having a female teacher is larger for subjects that are considered male dominated. If $\beta_i = 0$,

[3] The only exception to this happens when $N_j = 0$. Then, $h_{ii} = h_{ij} = \bar{h}$ even if $\alpha_t < 1$. This is further discussed in Section 2.3, where I analyze the effect of a female versus male teacher in gender segregated classrooms.

[4] An exception to this can happen if U is a linear or convex function and $N_1 = N_2$. If U is convex and half of the students in the class are girls, then both female and male teachers are indifferent between allocating all their time to boys or allocating all their time to girls. When teachers are indifferent, I will assume that they allocate all their time to boys.

the effect of having a female teacher does not depend on the subject.

Again, the critical assumption for the previous results is that α_t does not vary per subject. Alternatively, we could think of a different model where biased teachers select into different subjects. If $\alpha_{t,fav} > \alpha_{t,ag}$ (both female and male teachers have a larger bias against the other gender in male dominated subjects), then the effect of a female teacher on subjects that are male dominated is larger than the effect on subjects that are female dominated, even if $\beta_i = 0$. This could happen if the teacher bias is explained by gender stereotypes that influence teachers' behavior, and if these gender stereotypes differ by subject (if teacher bias is caused by preferences, it is not easy to justify why the teacher bias would differ per subject).

We can also compare the effect of having a female versus male teacher when the classroom is gender segregated. If there are only girls (boys) in the classroom, then the teacher will devote all his or her hours to girls (boys), i.e., $h_i = \bar{h}$. Then

$$E[S_{ii} - S_{ij}|mixed] - E[S_{ii} - S_{ij}|segregated] = l(f_i(h_{ii}^{mixed}, h_{ji}^{mixed}), \beta_i r_{iihs}) - l(f_i(h_{ij}^{mixed}, h_{jj}^{mixed}), \beta_i r_{ijhs}) - l(f_i(h_{ii}^{seg}, h_{ji}^{seg}), \beta_i r_{iihs}) + l(f_i(h_{ij}^{seg}, h_{jj}^{seg}), \beta_i r_{ijhs})$$

If $\alpha_t = 1$, the effect is the same whether the classroom is gender segregated or not. If $\alpha_t < 1$, then $h_{ii}^{mixed} > h_{ij}^{mixed}$ and $h_{ii}^{seg} = h_{ij}^{seg}$, so the effect of gender matching is smaller on gender segregated classrooms.

This last result is in line with Schneeweis and Zweimuller (2012) and Fryer and Levitt (2010). Schneeweis and Zweimuller argue that coeducational schools reinforce gender stereotypes because of "the lack of confidence of girls in subjects like math and science, the dominating behavior of boys in the classroom and an unequal treatment of boys and girls by teachers." Fryer and Levitt do not specify the mechanisms, but argue that mixed gender classrooms are a necessary component for gender inequality to translate into poor female math performance.

Again, a critical assumption for this result is that biased teachers do not select into gender segregated schools. If teachers in gender segregated classrooms are more biased than teachers in mixed classrooms, then we could find a zero (or larger) effect of female teachers in gender segregated classrooms if $\alpha_t < 1$.

Another assumption underlying the previous result is that gender segregated classrooms do not affect r_{ih}. However, the legitimation theory argues that mixed gender groups are male domains (Walker & Fennell, 1986), so the effect of role models can be greater in mixed gender groups. If this hypothesis is true, then mixed gender schools should have a negative effect on girls.[5] Unfortunately, the effect of mixed gender schools is difficult to estimate because better students could be selecting into gender segregated classrooms, and we do not observe the same student in both type of classrooms.

Although I cannot rule this explanation out, to my knowledge, the evidence for Chile that controls for selection suggests that it is not the case that mixed gender schools have a negative effect on girls. Urzúa and Zafar (2006) show that, controlling for selection, girls perform better in coeducational schools (they find that boys perform better in single sex schools), which provides evidence against this hypothesis. Moreover, although both girls and boys have higher scores in gender segregated schools, the increase is larger for boys.[6] If we assume that both girls and boys in gender segregated schools have similar unobserved characteristics, then this result does not support the legitimization theory.

A second way in which gender segregated classroom could be correlated with r_{ih} is if households with lower r_{ih} select into gender segregated schools. Then we would expect the effect of a female teacher to be larger in gender segregated schools, even if $\alpha_t = 1$.

Finally, if the teacher gender is more salient in mixed gender settings, then the effect of the female teacher should be larger in mixed gender schools, even if $\alpha_t = 1$.

3. Data

The System for Measuring the Quality of Education (SIMCE) test, created in 1998, is the main instrument with which the quality of education in Chile is measured. In 1999, the test was modified and standardized in order to follow up on school performance. The new test has an open ended scale that measures student abilities (cognitive skills). It uses the Item Response Theory (IRT) which is applied in most international tests of academic achievement (such as TIMSS or PISA) and links students' scores to their abilities. In 1999, it was also determined that the mean for that year would be 250, with a standard deviation of 50. The parameters of all subsequent evaluations have been calculated on the basis of the mean and variance of 1999.

The main variables used in this study come from SIMCE 2009. In 2009, SIMCE evaluated 239,745 students registered in 8th grade, and 5814 schools (MINEDUC, 2010), covering 92.5% of students and 98.2% of schools. Students took four tests at the end of the school year: Mathematics, Language and Communication, Social Sciences and Natural Sciences. In addition to census information on the four test scores, SIMCE 2009 collected data on characteristics of the student and the household, including student gender and parental education. The parent survey also asked for the main reasons for which the school was chosen.

SIMCE 2009 also surveyed the teachers responsible for teaching each student in the four academic subjects. The teacher survey solicited information about the teacher's characteristics and credentials, and how the teacher viewed the performance of her classroom.

[5] Riordan (1985), Bryk et al. (1993) and Eisenkopf et al. (2011) found a significant advantage to gender segregated schooling for girls. However, Doris et al. (2013) report evidence that the gender gap in mathematical performance is larger for children educated in single-sex schools than in coeducational schools.

[6] In the sample used in this study, the standardized score of students in gender segregated classrooms is, on average, 0.15 standard deviations higher than the score of students in integrated classrooms. The difference is 0.16 standard deviations for boys and 0.14 standard deviations for girls.

Table 1
Descriptive statistics.

Variables	Description	Mean	SD
Student and family characteristics			
# of students		119,489	
Simce	Standardized test score in subject	0.000	1.000
PastSimce	Past standardized test score in subject	0.000	1.000
PastGrade	Standardized past grade in subject	0.000	1.000
Male	Dummy for male student	0.493	0.500
FatherEduc	Father's education measured in number of years	11.443	3.777
Low	Father's education <8 years	0.248	0.432
Medium	Father's education between 8 and 12 years	0.467	0.499
High	Father's education >12 years	0.284	0.451
MotherEduc	Mother's education measured in number of years	11.361	3.576
Low	Mother's education <8 years	0.246	0.431
Medium	Mother's education between 8 and 12 years	0.480	0.500
High	Mother's education >12 years	0.273	0.446
Distance	Dummy for selected school because of distance	0.576	0.494
Teacher characteristics and credentials			
# of teachers		18,690	
FT	Female teacher	0.686	0.464
FEMFEM	Female student and female teacher	0.356	0.479
MALEMALE	Male student and male teacher	0.162	0.368
Specialization			
spe1	Teacher specialization missing	0.040	0.196
spe2	Equal to 1 if teacher has no specialization	0.451	0.498
spe3	Equal to 1 if teacher has specialization	0.509	0.500
Certification			
cer1	Teacher certification missing	0.014	0.118
cer2	Equal to 1 if teacher is not certified	0.020	0.140
cer3	Equal to 1 if teacher is certified	0.966	0.182
Experience			
exp1	Teacher experience missing	0.014	0.119
exp2	1–3 years of teacher experience	0.183	0.387
exp3	4–6 years of teacher experience	0.114	0.318
exp4	7–9 years of teacher experience	0.079	0.271
exp5	10–12 years of teacher experience	0.071	0.257
exp6	13–15 years of teacher experience	0.052	0.222
exp7	16–18 years of teacher experience	0.048	0.213
exp8	19–21 years of teacher experience	0.062	0.241
exp9	22–24 years of teacher experience	0.081	0.273
exp10	25+ years of teacher experience	0.310	0.462
Expectation			
expec1	Dummy for missing teacher expectations	0.022	0.146
expec2	Teacher expectations: 6 categories[a]	3.420	1.303
Classroom and subject characteristics			
# of classrooms		5999	
Math	Mathematics class	0.250	0.433
Lang	Language class	0.250	0.433
Nat	Natural Science class	0.250	0.433
Soc	Social Science class	0.250	0.433
GenderSeg	Dummy for gender segregated classrooms	0.095	0.293

Notes: The number of observations for all variables, except PastSimce, is 477,956. The number of observations for PastSimce is 305,418.
[a] expec2 = 1 when the teacher expects the majority of her students would not finish high school, and expec2 = 6 when the teacher expects the majority of her students to complete postgraduate studies.

Although SIMCE was not designed as a panel, information on past test scores for each student can be obtained from SIMCE 2005, when students where enrolled in 4th grade.[7] In 2005, SIMCE collected data on the test scores in three of the four subjects. Information on the previous year grades per subject is obtained from the Ministry of Education (MINEDUC).[8]

For this study, I use a sample of students with valid SIMCE 2009 scores, household characteristics and past grades, and for which the teacher survey is available. Due to non-response, information is available for 119,489 students, covering 51% of students.[9] A subsample with valid SIMCE 2005 scores is used to indirectly test the identification strategy. The variable means and standard deviations are presented in Table 1. For the purpose of this study, I standardize the scores, past scores and past grades in the sample by subject to a mean of zero and a standard deviation of one.

[7] Past SIMCE scores in each subject (with the exception of Social Sciences) are available for more than 85% of students.

[8] Information on past grades is missing for less than 4% of students.

[9] Nearly 29% of observations were lost due to missing teacher gender, 13% due to missing parental education, 4% due to missing past grades and 3% due to missing SIMCE test scores.

Table 2
2009 SIMCE scores and female teachers by gender and subject.

Average SIMCE score	Total	Subject			
		Math	Lang	Nat Sc.	Soc Sc.
Total	259.70	264.04	255.91	263.64	255.23
Boys	260.92	268.60	250.43	266.31	258.35
Girls	258.52	259.61	261.23	261.04	252.20
Raw difference	2.403	8.996	−10.808	5.269	6.155
	(0.147)	(0.296)	(0.290)	(0.292)	(0.290)
Standardized difference	0.047	0.175	−0.214	0.104	0.123
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
% of students with female teacher	68.63	58.86	81.08	73.44	61.13
% of classrooms with female teachers	66.95	56.98	79.53	71.35	59.94

Notes: Standard errors are presented in parentheses.

Because a high percentage of data is missing due to non-response, the external validity of the results could be compromised. Moreover, students in the sample have better observable characteristics than students not included in the sample.[10] To alleviate this concern, I use two larger samples to reestimate (when possible) the specifications used in this study. These two additional samples include students with no information on household characteristics. The first additional sample is a balanced panel of 150,257 students, covering 63% of students, and the second additional sample is an unbalanced panel of 722,130 observations and 201,872 students, covering 84% of students. The results were virtually unchanged.[11]

Table 2 documents the gender gap in raw scores and in standardized scores for my sample. The gender gap is 0.18 standard deviations in math, 0.12 in social sciences, 0.10 in natural sciences and −0.21 in language. The percentage of female teachers is lower in the subjects where boys perform better relative to girls, which is consistent with the idea that part of the gender gap might be explained by the gender of the teacher.

4. Econometric framework

As pointed out by several studies (see, for example Dee, 2007 and Clotfelter, Ladd, & Vigdor, 2010), the biggest challenge when estimating the effect of any teacher characteristic is that students and teachers may not be randomly assigned to classrooms. For example, higher achieving students could be assigned to female teachers, which would produce upward biased estimates of the effect of teacher gender.

Researchers have addressed this problem by using longitudinal data and incorporating student fixed effects. This strategy yields unbiased estimators, provided that students are not allocated to classrooms based on time varying unobserved propensity for achievement.

When only cross-sectional data is available, Dee (2007) proposes to estimate the effect of teacher characteristics, controlling for student fixed effects using the within student variation across subjects. Dee (2007) has two observations for the same student in different subjects, so he estimates the effect of teacher gender using first differences. In my case, I observe each student in four different subjects. This means that only the variation in teacher gender across subjects for each individual student is used to identify the effect of teacher gender.

To identify the effect of teacher–student gender matching, I estimate the following equation:

$$Y_{ijt} = \mu_i + MALEMALE_{ijt}\Gamma + FEMFEM_{ijt}\Pi + Z_{jt}\psi + \nu_{ijt} \quad (4)$$

where Y_{ijt} is the standardized test score for student i in subject j, with teacher t, μ_i is a student fixed effect and Z_{jt} is a vector of teacher and subject characteristics, including experience, certification and specialization, and subject fixed effects that are specific to the gender of the student. The variable $MALEMALE_{ijt}$ is equal to one if both student and teacher are male, and $FEMFEM_{ijt}$ is equal to one if both student and teacher are female. This specification allows the assignment to a same gender teacher to have the same achievement effects for both girls and boys ($\Gamma = \Pi$), or different effects ($\Gamma \neq \Pi$).[12]

The identification strategy used in this study requires sufficient variation in teacher gender within students. The variance decomposition of the gender of the teacher shows that the within student variation of teacher gender is larger than the variation of teacher gender between students. The within student variation of teacher gender accounts for more than 82% of the total variation, which is a considerable amount of variation that can be exploited in the empirical analysis.

As Dee (2007) argues, the main threat to identification when estimating the effect of teacher characteristics using the within student variation across subjects is that assignment to a female teacher may depend on students' subject specific propensity for achievement. The common practice of tracking by ability level could then bias the results.

To test whether this is the case, I follow Clotfelter et al. (2010) and run a regression of female teachers on a student

[10] For example, SIMCE, past grade, MothEduc and FathEduc are, respectively, 0.09, 0.03, 0.05 and 0.04 standard deviations higher for students in the sample.

[11] For presentation purposes, it is more straightforward to have the same sample through all regressions. Therefore, I present all of my results using the smaller sample.

[12] When $\Gamma = \Pi$, Eq. (5) simplifies to $Y_{ijt} = \mu_i + SAMESEX_{ijt}\theta + Z_{jt}\psi + \nu_{ijt}$, where SAMESEX is equal to one if the teacher and student share the same gender.

Table 3
Regression based test of identification strategy.

Variables	(1)	(2)	(3)	(4)
Past grade	0.005***	0.005***	0.0000	
	(0.001)	(0.001)	(0.002)	
Past grade × female student			0.009***	
			(0.003)	
Past SIMCE				0.000
				(0.003)
Past SIMCE × female student				−0.003
				(0.004)
Observations	477,956	477,956	477,956	305,418
R-squared	0.316	0.354	0.354	0.395
Student FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Subject FE		Yes	Yes	

Notes: Standard errors are presented in parentheses. The dependent variable in Models (1)–(3) is female teacher. The dependent variable in Model (4) is the residual of Model (3). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

fixed effects and past grades by subject, which I consider to be a proxy of subject specific propensity for achievement. Because the proportion of female teachers could vary by subject, I also include subject fixed effects as a control. Results are presented in Columns (1)–(3) in Table 3.

Table 3 shows that past grades do have an effect on the probability of being assigned to a female teacher, so the estimation of Eq. (4) would give biased results. Moreover, Table 3 shows that female students are more likely to be assigned to female teachers in subjects where their propensity for achivement is higher, so the effect of female teachers would have a positive bias for female students.

The advantage of my data set is that I can control for subject specific propensity for achievement using students' previous year grades by subject. Then, I can estimate the following equation:

$$Y_{ijt} = \mu_i + MALEMALE_{ijt}\Gamma + FEMFEM_{ijt}\Pi + Z_{jt}\psi + PastGrade_{ijt'}\phi_l + \nu_{ijt} \quad (5)$$

where $PastGrade_{ijt'}$ are the student's standardized grades in the previous year, and I allow the effect of past grades to vary by student gender, $l \in \{1,2\}$, where 1 denotes boys and 2 denotes girls.

The estimation of Eq. (5) would give unbiased results if, after controlling for past grades, the probability of being assigned to a female teacher is not related to subject specific propensity for achievement. To test this, I use the past test score as a second proxy for subject specific propensity for achievement, and test whether the past test score is correlated with female teachers after controlling for student fixed effects and past grades. The results of this test are presented in Column (4) in Table 3, where the dependent variable is the residual of the regression in Column (3). I find that the past score is not statistically significant, which is evidence in favor of the validity of my identification strategy.

A second concern in the estimation of the effect of teacher gender is that unobserved teacher characteristics may bias the results. Nixon and Robinson (1999) argue that, if the effect of a female teacher is negative or zero for boys, I can rule out explanations saying that female teachers are better teachers. In addition, I directly control for teacher unobserved characteristics by including teacher fixed effects:

$$Y_{ijt} = \mu_i + \kappa_t + MALEMALE_{ijt}\Gamma + FEMFEM_{ijt}\Pi + Z_{jt}\psi + PastGrade_{ijt'}\phi_k + \nu_{ijt} \quad (6)$$

where κ_t is a teacher fixed effect. This model is not identified unless I put some restrictions on Π or Γ, because the variable *MALEMALE* can be written as a linear combination of *FEMFEM*, the female students' fixed effects, and the male teachers' fixed effects. For the model to be identified, I need to impose either $\Pi = \Gamma$, or $\Gamma = 0$. This is further discussed in Section 5.

Eq. (6) will yield unbiased estimators provided that teacher gender is uncorrelated with the error term after including fixed effects and controlling for past grades. The results in Table 3 show that this is likely to be the case. To further test the validity of this assumption, I follow the idea in Rothstein (2010) that future teachers cannot have causal effects on past outcomes, whereas violations of model assumptions may lead to apparent counterfactual effects of this form. In particular, if $\nu_{ijt} = \mu_{ij} + \varepsilon_{ijt}$, where μ_{ij} is unobserved (time invariant) subject specific propensity for achievement, then we could find a significant effect of teacher gender in Eq. (7) if the assignment to a female teacher depends on subject specific propensity for achievement:

$$PastY_{ijt'} = \mu_i + \kappa_t + MALEMALE_{ijt}\Gamma + FEMEM_{ijt}\Pi + Z_{jt}\psi + PastGrade_{ijt'}\phi_k + \nu_{ijt} \quad (7)$$

Hence, if $\Gamma = \Pi = 0$, I cannot reject the validity of the assumption.

Finally, Dee (2007) argues that unobserved classroom traits could be correlated with gender, which would bias the results. However, in my data, students' homeroom classes are the same as the classes for each subject. This means that unobserved classroom traits are held constant across subjects for each student, so a model with student fixed effects adresses this concern.

5. Results

Table 4 shows the results for the effect of being assigned to a female teacher. Column (1) presents estimates using only school fixed effects and controls for parental education and student gender. Although specifications that do not control for student fixed effects are likely to yield biased estimates, I include them in Table 4 as a baseline. Columns (2) and (3) use student fixed effects. All specifications control for subject fixed effects specific to the student's gender, and teacher characteristics, such as experience, certification and specialization. Model (3) controls for the student's past grades as a proxy for the student's subject specific propensity for achievement.

In all specifications, the effect of the female teacher is positive and significant for girls, while the effect of the male teacher is not significant for boys.[13] The comparison

[13] The effect of the male teacher is only marginally significant in the model that does not control for student fixed effects.

Table 4
Estimated effects of female teachers on test scores.

Variables	(1)	(2)	(3)
Female teacher and student	0.035***	0.033***	0.031***
	(0.005)	(0.005)	(0.005)
Male teacher and student	−0.010*	−0.007	−0.007
	(0.005)	(0.005)	(0.005)
Past grade × male student			0.135***
			(0.004)
Past grade × female student			0.112***
			(0.003)
Observations	477,956	477,956	477,956
R-squared	0.318	0.802	0.806
Prob > *F*	0.165	0.108	0.055
School fixed effect	Yes		
Student fixed effect		Yes	Yes

Notes: Standard errors, clustered at the school level, are presented in parentheses. Model (1) includes controls for parental schooling and student gender. All models include controls for teacher characteristics and subject fixed effects specific to the student's gender. Prob > *F* refers to an *F*-test of the joint significance of the teacher controls. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

between models with student fixed effects and school fixed effects suggests that both girls and boys with an unobserved propensity for high achievement are more likely to be assigned to female teachers.

The results in Table 4 suggest that teacher–student gender matching has a positive effect for girls and no effect for boys. However, these results could be biased by the presence of unobserved teacher traits. Table 5 provides information about the different characteristics of female and male teachers. If teacher observed characteristics are correlated with teacher unobserved traits, and female teachers are better than male teachers, teacher quality, and not gender, could explain a positive effect of female teachers on student achievement. Table 5 shows that female teachers are more likely to have certification than their male counterparts, but are less likely to have a master's degree and have less experience on average. Overall, it is not clear whether female teachers are better than male teachers in observable characteristics.

Table 5 also shows the observable characteristics of classrooms with female teachers versus male teachers. Classrooms with female teacher have higher average parental education and the percentage of male students is lower (Lavy & Schlosser, 2011, show that an increase in the proportion of girls significantly improves students' cognitive outcomes). On the other hand, classrooms with female teachers are larger and the difference in past grades is not statistically significant. Overall, it is not clear whether classrooms with female teachers have better observable characteristics.

The results in Table 4 suggest that the effect of the teacher gender is zero for boys. Then, I can impose $\Gamma = 0$ to identify the effect of a female teacher on female students in a model that includes unrestricted teacher fixed effects, as in Eq. (6).

Column (3) in Table 6 presents estimates of Eq. (6), with the restriction that $\Gamma = 0$. The results show that, in the model where I include teacher and student fixed effects, the effect of being assigned to a female teacher is positive and statistically significant for girls, although it is smaller than the effect in the model where I do not control for unobserved teacher characteristics (Column 2 in Table 6). The reduction is statistically significant, which indicates that there is a positive bias in the results of the model that does not control for teacher characteristics.

To further test the validity of the identification strategy, I estimate the effect of a female teacher on past test scores. Mores especifically, the test involves reestimating Eq. (6) after replacing each student's test score in 8th grade with their 4th grade test score, as in Eq. (7). This test follows the idea in Rothstein (2010) that future teachers cannot have causal effects on past outcomes. However, if the assigment to a female teacher in 8th grade is associated with large gains in 4th grade achievement, it would be evidence that the estimates in Table 6 are biased.

Column (1) in Table 7 reestimates the coefficients of Table 6 for the subsample of student with valid past test scores, and Column (2) shows the results for the model

Table 5
Teacher and classroom characteristics by teacher gender.

	Female teachers	Male teachers	Difference
Teacher characteristics			
Years of experience	16.562	17.843	−1.280
			(0.199)
% of teachers with certification	0.982	0.972	0.010
			(0.002)
% of teachers with specialization	0.527	0.544	−0.016
			(0.008)
Classroom characteristics			
Proportion of male students	0.491	0.517	−0.027
			(0.003)
Number of students	20.417	18.907	1.511
			(0.131)
Mean past grade	0.030	0.028	0.002
			(0.007)
Mean mother's schooling	11.028	10.707	0.321
			(0.037)
Mean father's schooling	11.118	10.767	0.351
			(0.039)

Notes: Standard errors are presented in parentheses.

Table 6
Estimated effects of female teachers on test scores: teacher fixed effects.

Variables	(1)	(2)	(3)
Female teacher and student	0.031***	0.031***	0.018***
	(0.005)	(0.005)	(0.005)
Male teacher and student	−0.007		
	(0.005)		
Past grade × male student	0.135***	0.135***	0.182***
	(0.004)	(0.004)	(0.003)
Past grade × female student	0.112***	0.112***	0.169***
	(0.003)	(0.003)	(0.003)
Observations	477,956	477,956	477,956
R-squared	0.806	0.806	0.828
Student fixed effect	Yes	Yes	Yes
Teacher fixed effect			Yes

Notes: Standard errors, clustered at the school level, are presented in parentheses. All models include subject fixed effects specific to the student's gender. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table 7
Estimated effects of female teachers on test scores and past test scores.

Variables	Score	Past score
Female teacher and student	0.017**	−0.005
	(0.007)	(0.007)
Past grade × male student	0.210***	0.143***
	(0.005)	(0.004)
Past grade × female student	0.196***	0.144***
	(0.004)	(0.004)
Observations	305,418	305,418
R-squared	0.856	0.864
Student fixed effect	Yes	Yes
Teacher fixed effect	Yes	Yes

Notes: Standard errors, clustered at the school level, are presented in parentheses. All models include subject fixed effects specific to the student's gender. All models are estimated using the subsample of students with valid past test scores. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8
Teacher expectations.

Variables	OLS	Oprobit	OLS	Oprobit
% male[a]	−0.883***	−0.740***	0.389***	0.392***
	(0.116)	(0.097)	(0.107)	(0.095)
Female teacher	0.150	0.122	0.110	0.083
	(0.145)	(0.121)	(0.091)	(0.077)
Female teacher × % male	−0.056	−0.057	−0.350***	−0.319***
	(0.078)	(0.064)	(0.130)	(0.114)
Mean grade	0.557***	0.474***	0.728***	0.646***
	(0.018)	(0.015)	(0.060)	(0.053)
Observations	21.443	21.443	2.026	2.026
R-squared	0.054	0.019	0.095	0.037
Segregated classroom	No	No	Yes	Yes

Notes: Standard errors are presented in parentheses. The dependent variable is coded in 6 categories, where Expec = 1 when the teacher expects the majority of her students would not finish high school, and Expec = 6 when the teacher expects the majority of her students to complete postgraduate studies. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a] In segregated classrooms, the variable %male can only take values of 0 and 1.

where the dependent variable is past test scores. I can reject that the teacher in 2009 had an effect on the 2005 score, which is evidence in favor of the validity of my identification strategy.

6. Possible mechanisms

6.1. Teacher bias and self selection

As discussed in Section 2, if the effect of the female teacher is due to teachers providing a role model or is due to the theory of stereotype threats, we would expect a larger effect for girls in subjects that are considered male dominated: we should observe a larger effect of female teachers in math and a smaller effect in language. Also, we would expect to see a larger effect on girls who do not have other strong female role models. If the positive effect of the female teacher on girls is due to teacher behavior, then we would not necessarily see a different effect by subject or for girls without other strong female role models. Finally, if it is due to teacher bias, we would expect to see a larger effect in mixed gender classrooms.

These results depend on the assumption that biased teachers do not sort to schools with lower levels of parental education, that biased teachers are randomly distributed across subjects, and that biased teachers do not sort to gender segregated schools.

To test these assumptions, I use data on teacher's expectations about the classroom. Teachers are asked what level of education they expect the majority of their students to reach.[14] To study the difference in teacher bias between male and female teachers, I study how the expectations vary for male and female teachers as the percentage of male students in the classroom increases. If teachers are biased, then, as the percentage of male students increases, female teachers should lower their expectations while male teachers should increase their expectations. If teachers are unbiased, then the difference in expectations between male and female teachers should remain constant as the percentage of male students in the classroom increases. Thus, female and male teachers do not have different biases if α_3 in Eq. (8) is equal to zero:

$$Expec_{jt} = \alpha_0 + \alpha_1 FT_{jt} + \alpha_2 \%Male_{jt} + \alpha_3 \%Male_{jt} FT_{jt} + \alpha_4 MeanPastGrade_{jt}\phi + \varepsilon_{jt} \quad (8)$$

where *Expec* are the teacher expectations about her classroom, *FT* equals 1 if the teacher is female, *%Male* is the percentage of male students in the classroom, and MeanPastGrade is the average past grade by subject in the classroom. The results of estimating Eq. (8) for the subsample of 21,443 mixed gender classrooms show no evidence of differences in teacher bias (Column 1 in Table 8). Both female and male teachers lower their expectations when the percentage of male students increases, and I cannot reject no difference in teacher bias between male and female teachers. More importanty, this result does not change when I allow α_3 in Eq. (8) to vary by subject or by different levels of parental schooling.[15] For the subsample of 2614 gender segregated classrooms, α_3 is negative and statistically significant (Column 3, Table 8). Because in gender segregated classrooms the variable *%Male* can only take values of zero and one, this can be interpreted as a difference in bias in schools with only male students. In particular, I find that male teachers have higher expectations for boys in gender segregated schools ($\alpha_3 < 0$). Thus, there might be a greater bias of male teachers in favor of boys in gender segregated schools due to teacher sorting. These results do not change when I estimate Eq. (8) using an ordered probit, to take into

[14] Answers are coded in 6 categories, where *Expec* = 1 when the teacher expects the majority of her students would not finish high school, and *Expec* = 6 when the teacher expects the majority of her students to complete postgraduate studies.

[15] To test this, I interact $\%Male_{jt}FT_{jt}$ in Eq. (8) with subject and with parental education. In both cases, the *F* test cannot reject a jointly zero effect at all conventional significance levels.

account that the dependent variable is categorical (Columns 2 and 4 in Table 8).

6.2. Role model or teacher bias?

The positive effect of female teachers on girls achievement could be due to teacher behavior or student behavior. Teacher bias may lead female teachers to spend more time on girls in the classroom, which helps female students to achieve higher scores. On the other hand, female teachers may play a role as a positive role model for female students, which also helps girls to achieve higher test scores.

If the teacher bias explanation is true, we would expect a larger effect on gender mixed classrooms. To test this hypothesis, I construct a dummy variable for gender segregated classrooms, *GenderSeg*, and include this variable and the interaction between this variable and the gender of the teacher in the following regression:

$$Y_{ijt} = \mu_i + GenderSeg_{jt}\lambda + FT_{jt}\Pi_1 + FT_{jt}GenderSeg_{jt}\Pi_2 + Z_{jt}\psi + PastGrade_{ijt'}\phi_l + \nu_{ijt} \quad (9)$$

where *FT* equals 1 if the teacher is female. The results of estimating Eq. (9) separately for boys and girls are presented in Table 9. The interaction between gender segregated classrooms and female teachers is negative and not significant for boys and positive and not significant for girls. This result goes in the opposite direction of the hypothesis, so it is evidence that the effect of the teacher is not due to teacher bias.

As discussed in Section 2.3, a smaller effect of female teachers in gender segregated schools could be explained by teacher bias, by the legitimation theory and by the gender of the teacher being more salient in mixed gender classrooms, while a larger effect of female teachers in gender segregated classrooms could be explained by households with lower r_{ih} selecting into gender segregated schools, and biased teachers selecting into gender segregated schools. Then, if there is teacher bias but students and teachers are selecting to gender segregated schools, the two effects could cancel out. Therefore, I need to rule out selection of students and teachers to gender segregated schools for the test to reject teacher bias.

The evidence presented in Section 6.1 showed that there is no evidence of selection of biased female teachers into gender segregated schools, but there is evidence that male teachers in boys' schools have higher expectations for their classrooms than female teachers. This difference in bias could explain the negative coefficient of the interaction between gender segregated classroom and female teachers for boys, although it is not statistically significant. Because the results throughout the paper have been only positive for girls, I would not worry much about the selection of male teachers to boys only schools, since the gender of the teacher does not seem to have an effect on boys.

As discussed before, if households with lower r_{ih} select into gender segregated schools, we would expect a larger effect of female teachers in gender segregated schools due to a role model effect. To rule this out, I reestimate the results in Table 9 for the subsample of students whose parents declared to have chosen the school because of distance. The signs of the interaction between gender segregated classrooms and female teachers are the same as for the full sample.

Table 9
Estimated effects of female teacher on test scores by gender-segregated classrooms.

Variables	Boys		Girls	
	(1)	(2)	(1)	(2)
Female teacher in gender	−0.016	−0.019	0.021	0.008
Segregated classroom	(0.024)	(0.033)	(0.022)	(0.030)
Female teacher	0.008	0.002	0.029***	0.029***
	(0.005)	(0.006)	(0.005)	(0.006)
Past grade	0.135***	0.134***	0.112***	0.110***
	(0.004)	(0.004)	(0.003)	(0.004)
Observations	235,484	136,304	242,472	139,036
R-squared	0.803	0.792	0.809	0.798
Prob > *F*	0.0738	0.260	0.148	0.307

Notes: Standard errors, clustered at the school level, are presented in parentheses. All models include student fixed effects, controls for teacher characteristics and subject fixed effects specific to the student's gender. Prob > *F* refers to an *F*-test of the joint significance of the teacher controls. Model (1) uses data for the whole sample while model (2) uses data for students whose parents declared to have chosen the school because of distance. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Overall, the evidence presented in Table 9 and Section 6.1 rejects the hypothesis that the positive effect of female teachers on girls is explained by teacher bias.

The specifications presented in the previous sections assume that the effect of being assigned to a female teacher is independent of the subject being taught. Alternatively, and consistent with the role model hypothesis, a female teacher has a larger effect for girls in subjects that are considered male dominated. Table 2 shows the percentage of female teachers by subject. Although there are more female teachers in every subject, the percentage is lower in math and higher in language. This is consistent with the belief that math is a male dominated subject while language is a female dominated subject.

To test the hypothesis that the effect of the female teacher is larger in subjects that are male dominated, I estimate the following equation:

$$Y_{ijt} = \mu_i + \kappa_t + FEMFEM_{ijt}\Pi_j + Z_{jt}\psi + PastGrade_{ijt'}\phi_k + \nu_{ijt} \quad (10)$$

where I allow the effect of the female teacher to differ by subject. Results are presented in Table 10. The results in the first column of Table 10 are based on a version of Eq. (10) that excludes the teacher fixed effect, so I can allow teacher gender to have an impact on boys. For boys, the effect of being assigned to a female teacher is not significantly different from zero for any subject when using student fixed effects. For girls, the effect is positive and significant for all subjects except for language, where the effect is positive but not significant. The effect is greater for mathematics and social sciences, which are the subjects with lower percentages of female teachers, as shown in Table 2. These are also the subjects where the gender gap is larger. Interestingly, the only subject where

Table 10
Estimated effects of female teachers in test scores by subject.

Variables	(1)	(2)	(3)
Female teacher and student in math	0.050***	0.050***	0.029***
	(0.010)	(0.010)	(0.009)
Female teacher and student in language	0.011	0.011	0.006
	(0.012)	(0.012)	(0.011)
Female teacher and student in nat. sc.	0.025***	0.025***	0.015*
	(0.009)	(0.009)	(0.009)
Female teacher and student in soc. sc.	0.027***	0.027***	0.016*
	(0.009)	(0.009)	(0.009)
Male teacher and student in math	−0.004		
	(0.010)		
Male teacher and student in lang	−0.001		
	(0.011)		
Male teacher and student in nat. sc.	−0.013		
	(0.011)		
Male teacher and student in soc. sc.	−0.008		
	(0.010)		
Past grade × male student	0.135***	0.135***	0.182***
	(0.004)	(0.004)	(0.003)
Past grade × female student	0.112***	0.112***	0.169***
	(0.003)	(0.003)	(0.003)
Observations	477,956	477,956	477,956
R-squared	0.806	0.806	0.828
Student fixed effect	Yes	Yes	Yes
Teacher fixed effect			Yes

Notes: Standard errors, clustered at the school level, are presented in parentheses. All models include subject fixed effects specific to the student's gender. $^*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11
Estimated effects of female teachers in test scores by parents' education.

Variables	(1)	(2)	(3)
Female teacher and student			
Mother's education			
Low	0.0314***	0.0419***	0.006
	(0.012)	(0.008)	(0.011)
Medium	0.0278***	0.0357***	0.0162*
	(0.010)	(0.006)	(0.009)
High	0.008	0.011	0.010
	(0.009)	(0.008)	(0.009)
Male teacher and student			
Father's education			
Low	−0.021		
	(0.013)		
Medium	−0.0179*		
	(0.011)		
High	0.009		
	(0.010)		
Past grade × male student	0.135***	0.135***	0.182***
	(0.004)	(0.004)	(0.003)
Past grade × female student	0.112***	0.112***	0.169***
	(0.003)	(0.003)	(0.003)
Observations	477,956	477,956	477,956
R-squared	0.806	0.806	0.828
Student fixed effect	Yes	Yes	Yes
Teacher fixed effect			Yes

Notes: Standard errors, clustered at the school level, are presented in parentheses. All models include subject fixed effects specific to the student's gender. $^*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

the effect of the female teacher is not significant is language, which is also the only subject where girls outperform boys.[16] In Column (3), I include teacher fixed effects. The effect of the female teacher on female students is lower than in the model without teacher fixed effects, but still positive and statistically significant for all subjects except for language.

If the role model hypothesis is true, the effect should be greater for girls who are lacking other positive female role models. To test this, I divide the sample of girls by mother's education and create an indicator if the mother has less than 8 years of education (no high school), between 8 and 12 (some high school to high school graduate), and 12 or more years (at least some years of college or professional school). For boys, I divide the sample by father's education. Results are presented in Table 11. For boys, the effect of the male teacher is only marginally significant for medium levels of father's education (the p-value is equal to 0.099). In the model without teacher fixed effects, the effect of a female teacher is positive and significant for girls with low and medium levels of mother's education, and positive but not significant for girls with high mother's education. However, in the model with teacher fixed effects, the effect of a female teacher is only significant for girls with medium levels of mother's education.

Overall, the results in Table 11 suggest that being assigned to a female teacher has no effect for girls with high levels of mother's education. However, being assigned to a female teacher has no effect for girls with low levels of mother's education in models that control for teacher fixed effects. Although this is not consistent with the prediction in Section 2.3, the model can be easily modified to incorporate this result. We just need to add that the function g described in (3) is such that $(\partial^2 g/\partial r_{it}\partial r_{ih}) < 0$ for $r_{ih} \geq \bar{r}_h$. This means that the household and teacher role models can be seen as complements for low levels of household role models, and substitutes for higher levels.

7. Conclusions

In this study, data from the Chilean SIMCE test has been used to empirically estimate a reduced form equation, shedding some light on one of the components of the gender gap for students. The results show that there is an effect of the gender of the teacher on the scores of female students. Having a female math teacher increases the average scores of female students in the SIMCE test by approximately 0.04 standard deviations, which is almost one fourth of the gender gap in math. However, there is no evidence of an effect of teacher gender on boys' scores.

My results differ from those previously found by Dee (2007) because I do not find an effect for male students. They also differ from the results in Cho (2012). My results

[16] Although a greater effect in mathematics is consistent with the role model hypothesis, it could be explained with a greater sensitivity of mathematics to interventions in general. To test this, I allow the effect of teacher certification, experience and specialization to differ by subject. Certification does not have an effect on student achievement for any subject, but specialization does have a positive effect on student achievement. Moreover the effect of teacher specialization is only significant in language and social sciences. For experience, I find a positive effect in language and a negative effect in social sciences. Overall, I can reject a greater sensitivity of mathematics to interventions in general.

are closer to those of Nixon and Robinson (1999), who find that a higher proportion of female faculty has a positive effect on females attending high schools, while there is no effect on male students.

Cho (2012) argues ''that the advantages of teacher–student gender matching on student achievement has diminished over the last two decades in the United States, especially in math and science subjects.'' This can be explained by my model as an increase in r_{is} in math and science for girls. In other words, as society stops viewing math and science as male dominated subjects, the effect of teacher–student gender matching diminishes. This has probably been the case in the United States, where the percentage of female teachers in these subjects increased 7–9 percentage points between 1988 and 2007 (see Cho, 2012, Table A2 and A3). Thus, the difference between my results and those of Cho (2012) may be due to the society and family components of the role model effect. Alternatively, it could be due to a difference in the methodology, since my study is able to control for subject specific ability.

The evidence is consistent with the role model hypothesis, because the effect is only significant for subjects with lower proportions of female teachers, and we see no effect for girls with higher levels of mother's education. The effect is also larger or the same for gender segregated classrooms, which is evidence against teacher bias.

Finally, note that I analyze the effect of teacher bias on standardized test scores, where teachers do not grade their students' exams. Teacher behavior will probably have a larger impact on course grades and subjective teacher evaluations and expectations, where teachers can not only allocate their effort toward one group, but, in addition, can actively discriminate against a group by giving them lower grades. Examples of studies that analyze the effect of teacher bias on grades are Lavy (2008) and Hinnerich, Hoglin, and Johannesson (2011). However, these studies do not separate between male and female teachers.

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