Stereotypes, Role Models, and the Formation of Beliefs

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Abstract

Stereotypes can erroneously reduce children's beliefs about their own ability, negatively affecting effort in school and investment in skills. Because of dynamic complementarity in the formation of human capital, this may lead to large negative effects on later life outcomes. In this paper, we show evidence that role models, in the form of female math teachers, can counter the negative effects of gender-based stereotypes on girls' perceptions of their math ability. A simple model of investment in human capital under uncertainty predicts the greatest effects of role models accruing to girls who perceive themselves to be of low ability. We exploit random assignment of students to classes in Chinese middle schools to test this prediction, examining the effects of teacher-student gender match on students' perceived ability, aspirations, investment, and academic performance. We find that, for girls who perceive themselves to be of low ability, being assigned a female math teacher causes large gains in all of these outcomes. We see no effects of teacher-student gender match on children who do not perceive themselves to be of low math ability. We show evidence against the potential alternative explanations that differential teacher effort, skill, teaching methods, or differential attention to girls drive these effects.

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1 Introduction

As a person goes through life, her beliefs are shaped by what she comes in contact with, and these beliefs in turn inform her investment decisions. A long line of both empirical and theoretical work has explored the importance of this causal chain in the formation of human capital (Becker, 1975; Jensen, 2010; Lybbert and Wydick, 2016b; Genicot and Ray, 2017). Because human capital formation is characterized by dynamic complementarity, this link from information to beliefs and on to human capital investment decisions is particularly important in the early stages of life (Cunha and Heckman, 2007).

If a child is incorrectly told she is of low ability in a given subject (relative to other subjects), the principle of comparative advantage predicts she will decrease investment in that subject. This then generates a self-fulfilling prophecy - because of the nature of human capital formation, her investment decision in period one means that in period two she will be relatively less able in the subject, thus bearing out the prediction of the misinformation. A common source of such misinformation is negative stereotypes about ability by gender and ethnicity (Steele and Aronson, 1995; Steele, 2003). Recent evidence from psychology suggests that gender stereotypes affect interests and time use decisions of both girls and boys as early as age seven (Bian et al., 2017) and that such stereotypes may lead to underrepresentation of women and minorities in several scientific fields where these biases persist (Leslie et al., 2015).

In this paper, we study how beliefs are affected by stereotypes and role models, and how this influences aspirations, investment in skills, and academic performance. Specifically, we provide evidence from Chinese middle schools on the potential for female math teachers to protect against the negative effects of the common stereotype that girls are worse than boys at mathematics. In our setting, there is widespread belief among children that boys are better than girls in learning math. We exploit random assignment of students to classrooms to estimate the effect of teacher-student gender match on girls' and boys' beliefs, behaviors, and academic outcomes, by perceived ability. For girls who perceive themselves to be of low ability in math, we find large positive effects of being assigned a female math teacher on these girls' perceived ability, aspirations, investment in human capital, and performance in mathematics. We see no gender-specific benefit for girls who do not perceive themselves to be of low ability in math. We then conduct a series of analyses that together suggest the effects we observe are driven by a particular mechanism: female math teachers serve

as role models for low perceived ability girls.

We motivate our empirical analysis by deriving predictions from a simple conceptual framework based on the model of aspirations and aspiration frustration in Genicot and Ray (2017). In our model, students make forward-looking human capital investment decisions based on their perceived return to investment, which is a function of their ability endowment and the information they have encountered up to that point. We model students as Bayesians who update their beliefs about the returns to investment in human capital based on the information they come in contact with as they proceed through schooling. Negative and incorrect information (e.g., negative stereotypes, a negative stochastic shock in information about ability, or not having credible evidence of the returns to schooling) can reduce the perceived net returns to investment in human capital. This change in perception, in turn, can lead to suboptimal investment behavior and later life outcomes[1]. As students in China proceed from primary to middle school, the difficulty of math increases and this increases the perceived cost of investment in math-related human capital. The main prediction of our model is that for girls who perceive themselves to be of low ability in math, we expect the provision of a teacher in this difficult subject who shares an identity with these girls (by virtue of shared gender) to lead to larger gains in beliefs, aspirations, investment in human capital, and performance than for any other configuration of student gender, student perceived ability, and teacher gender.

We test these predictions using data from the baseline wave of the China Education Panel Survey (CEPS), a nationally representative survey of Chinese middle school students. The survey collected information from school administrators on whether students are randomly assigned to classrooms or are assigned to classrooms through non-random mechanisms (mostly tracking). This allows us to estimate the causal effects of different classroom configurations, a method one of us has used in previous work to study peer effects in these classrooms (Hu, 2015). The CEPS also elicited detailed information on student-teacher interactions in the classroom, student time use, teacher time use, and teaching methods. These data make it possible to explicitly investigate underlying mechanisms probed only indirectly in other work on the impact of teacher-student gender match on girls (Dee, 2007; Carrell et al., 2010; Paredes, 2014; Antecol et al., 2015; Lusher et al., 2015). In line with the predictions of our conceptual framework, we find low perceived ability girls assigned to female math teachers are 20 percentage points less likely to perceive math as "very

[1]The work of William Julius Wilson has hypothesized that lack of positive role models is one reason for low investment in human capital in inner city America (Wilson, 2012).

difficult" (from a baseline of 80%), are 11 percentage points less likely to aspire to jobs in the visual or language arts (baseline 23%), and are 9 percentage points more likely to enroll in mathematics tutoring (baseline 15%). These girls also perform 0.45 standard deviations better on a standardized math test.

We argue that an important channel for these observed effects is that the math teacher serves as a role model, protecting low perceived ability girls against the harmful effects of negative gender stereotypes. First, we see no effect of providing a female math teacher on the beliefs, aspirations, investment behavior, or performance of girls who do not perceive themselves to be of low ability when they are assigned math teachers of the same gender. Second, we conduct several analyses showing no evidence for the competing hypothesis that differential teacher aptitude, teaching methods, or teacher effort drives these effects. We also test for the possibility that female teachers give extra attention, either praise or opportunity to practice in class, to low perceived ability girls, and find no evidence of this possible alternative explanation for our main results. Finally, consistent with the psychological concept of "identity threat" (Steele et al., 2002; Sherman et al., 2013), we also find that low perceived ability boys assigned to female math teachers report increased perceived difficulty of mathematics.

We contribute to two active literatures. The first is the budding set of studies on the formation of aspirations and beliefs and their role in forward-looking decisions, particularly those related to human capital formation. Several recent papers, both empirical (Bernard et al., 2014; Lybbert and Wydick, 2016a; Ross, 2016) and theoretical (Akerlof and Kranton, 2000, 2002; Bénabou and Tirole, 2011; Lybbert and Wydick, 2016b), have studied the role of aspirations in affecting investment behavior. To this work, we add empirical evidence of an important informational channel through which beliefs and aspirations can be influenced. Our results are consistent with both the hypothesis of Wilson (2012) and a key prediction of the model in Genicot and Ray (2017); namely, that informational shocks about oneself (as opposed to about the world, as in Jensen, 2010) may induce changes in aspirations, which in turn lead to changes in investment and outcomes. Our analysis contributes novel evidence on the protective effect role models can have on the formation of the beliefs and aspirations of students facing negative stereotypes at a crucial stage of child development.

The second area we contribute to is the long-standing literature studying the effects of teacher-student identity match on the performance of stereotyped-against individuals (e.g., Bettinger and

Long 2005; Dee 2007; Carrell et al. 2010; Fairlie et al. 2014; Gershenson et al. 2016; Muralidharan and Sheth 2016). While this literature has argued for and shown evidence of several possible mechanisms driving the largely positive effects found, we provide the first direct evidence we are aware of in support of a specific mechanism, the power of role models to shape beliefs, in driving the positive effects of teacher-student gender match on student test scores. Furthermore, unlike many previous studies on teacher-student gender match, we study a setting where, overall, girls perform slightly better than boys in mathematics. Nonetheless, negative gender norms about girls' math ability persist, and are strongest among the low perceived ability girls. It is precisely among these girls that we see the largest impact of having a female math teacher.

The rest of this paper is structured as follows. In Section 2 we outline our conceptual framework to motivate the focus of the paper on low perceived ability girls. Section 3 describes the setting we study. Section 4.1 outlines our data sources and provides summary statistics of our main variables. Section 4.2 introduces our empirical strategy and presents results for tests of our main identifying assumptions. Section 5 presents our main empirical results estimating the effects of being assigned a female math teacher on student beliefs, aspirations, investment, and performance. Section 6 investigates possible mechanisms for these effects and discusses the limitations of our study. The final section concludes.

2 Conceptual framework and empirical motivation

This section motivates our empirical analysis. First, we describe a simple conceptual framework, drawing on Genicot and Ray (2017), which generates predictions that we test later in the paper. We then conduct a simple distributional difference test using our data which further motivates the empirical focus on low perceived ability girls.

Both across countries and in our Chinese data, girls express a disproportionate lack of confidence in their own ability in math as well as in the math ability of their gender (Beilock et al., 2010; OECD, 2015). The empirical literature in psychology demonstrates that these "gender-stereotyping" beliefs in girls can directly contribute to worse performance via two channels. First, anxiety because of "stereotype threat" (Shih et al., 1999; Spencer et al., 1999; Niederle and Vesterlund, 2010; Cheryan, 2012) could lead to lower performance on high stakes math assessments, which would in turn affect later life outcomes. Second, negative gender norms may exert downward pressure

on beliefs in the returns to investment, causing girls to invest less effort, enthusiasm, and time in studying for math, thus generating a self-fulfilling prophecy (Bian et al., 2017). A corollary of these findings is that the presence of a female teacher in the same subject as the stereotypical belief could change girls' views about the potential positive returns to their effort in math. The female teacher provides a credible (by virtue of shared gender) example of the returns to such effort (Carrell et al., 2010; Wilson, 2012; Genicot and Ray, 2017) which, in turn, may change girls' willingness to exert effort in the subject area (Nixon and Robinson, 1999; Beaman et al., 2009; Gunderson et al., 2012). Evidence from psychology also suggests that such an example could lead to an increase in students' academic motivation and expectations (Nixon and Robinson, 1999; Gershenson et al., 2016).

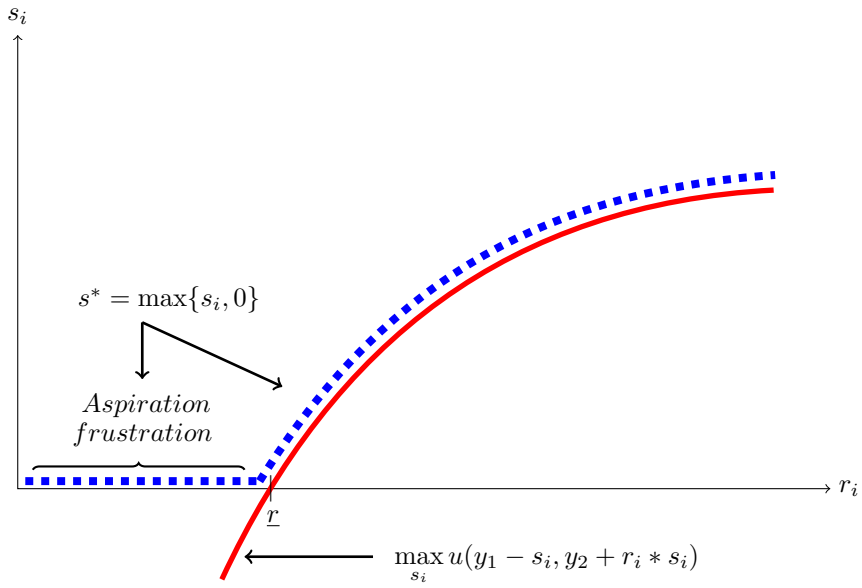
To formalize this intuition and motivate our empirical work, we place our analysis in the context of a simple two period model of consumption and savings. Imagine an individual with the following consumption problem over two periods:

$$\max_{s_i} u(y_1 - s_i, y_2 + r_i * s_i) \tag{1}$$

We assume utility from consumption is concave in both periods. Defining terms, y_t is income in period t, s_i is the savings of individual i in period 1, and r_i is individual i's belief about her return on saving in period 1, earned in period 2. The savings technology is investment in human capital, and we assume that an individual cannot borrow against the future. We assume r_i is a function of the individual's endowment and the informational environment the individual faces, which can include information gleaned from parents, peers, the media, societal stereotypes, and so forth. The link to the Genicot and Ray model is through r_i. We assume there is a range $[0, \underline{r})$ over which the interest rate does not justify investment. For some of the individuals whose perceived return on investment falls in this range, this will be the result of incorrect information, either stochastic shocks or systematic biases such as stereotypes. These individuals will rationally but suboptimally choose not to invest in human capital, part of what Genicot and Ray call "aspiration frustration." In Figure 1, we depict this static part of our model graphically.

The effect of new information on the update to r_i will depend on two parameters of the signal, its credibility and the difference between the individual's prior and the new information provided by the signal. Informally, for girl students who perceive themselves to be of sufficiently low ability in

Figure 1: Visual depiction of the model



math that they fall into the aspiration frustration part of the support of r_i, being assigned a female math teacher provides a signal of the potential for returns to investment in human capital that is credible because of the teacher's shared gender, and far from these girls' priors, which have been formed both by gender stereotypes and the low signals about ability received up to that point. For other students, the combination of positive signals (girls and boys who are doing well in math) and a lack of negative stereotypes (all boys) lead to the prediction that being assigned a same-gendered math teacher is unlikely to cause these individuals to update r_i in response to a female teacher as dramatically as will low perceived ability girls.

Formally, individual i proceeds through life gaining new information about r_i from her environment and experiences. For convenience we divide beliefs about r_i into a discrete variable A_i:

$$A_i = \begin{cases} L & if \quad r_i < \underline{r} \\ H & if \quad r_i \geq \underline{r} \end{cases} \tag{2}$$

Our object of interest is a set of conditional probabilities $P(H|G^i, P^i, T^i)$, where the conditions relate to the gender of the student, her/his perceived ability in mathematics, and the gender of the middle school math teacher. We define student gender as $G^i \in \{G^g, G^b\}$, where g and b indicate the student is a girl or a boy, respectively. We define student perceived ability as $P^i \in \{P^l, P^h\}$,

where l and h indicate the student perceives herself to be of low or high ability, respectively. We define teacher's gender as $T^i \in \{T^f, T^m\}$, where f and m indicate the teacher is female or male, respectively. In the data we see that $P(H|G^g) < P(H|G^b)$, that is, girls have lower perceived ability in math than boys[2]. In addition, we make two assumptions that allow us to generate three predictions to test in our data.

Assumption 1: $P(G^g, T^f|L) < P(G^g, T^f|H)$, that is, the probability of encountering a same-gendered math teacher is higher if $A_i = H$ than if $A_i = L$. This generates a mapping from $P(H|G^g)$ to $[P(H|G^g, T^f) - P(H|G^g)]$ that has an inverse-U shape with a longer right tail. We show an example of this in Figure A.1.

Assumption 2: $P(H|G^g, T^f) - P(H|G^g) > P(H|G^g, T^m) - P(H|G^g)$, that is, the signal sent by female teachers to girl students is more likely to cause girls to update than that sent by male teachers to girl students. This stems from the assumption that the shared gender identity of teacher and student increases the credibility of the signal sent by the teacher, and is supported by previous work on teacher-student gender match (Carrell et al., 2010; Paredes, 2014; Muralidharan and Sheth, 2016).

Prediction 1: $P(H|G^g, P^l, T^f) - P(H|G^g, P^l) > P(H|G^g, P^h, T^f) - P(H|G^g, P^h)$, that is, we predict low-perceived ability girls will make larger updates to their prior than high perceived ability girls in response to encountering a female teacher. This prediction comes from Assumption 1, and is derived from a basic tenet of information theory: information that is relatively new to the receiver generates a larger update to the prior than it would for receivers for whom the information is less novel[3]. Seen through the lens of Bayesian updating, high perceived ability girls have a much higher $P(H)$ than low perceived ability girls, and so stand to update far less than low perceived ability girls from the same information.

Prediction 2: $P(H|G^g, T^f) - P(H|G^g) > P(H|G^b, T^*) - P(H|G^b)$. In prose, we predict that girls assigned to a female math teacher should update their prior on their ability to productively invest more than boys assigned to either a female or male math teacher. This is a direct consequent of girls' lower perceived ability and Bayes' rule.

Corollary: depending on the proximity of r_i to $\underline{r}$, we should also see gains in s_i and academic

[2]Given that girls have slightly better math test scores than boys, we conclude that at least some of the gap in perceived ability is due to negative gender stereotypes.

[3]That is, low perceived ability girls exposed to an example of success see it as more novel than do high perceived ability girls, who in themselves already have an example of success.

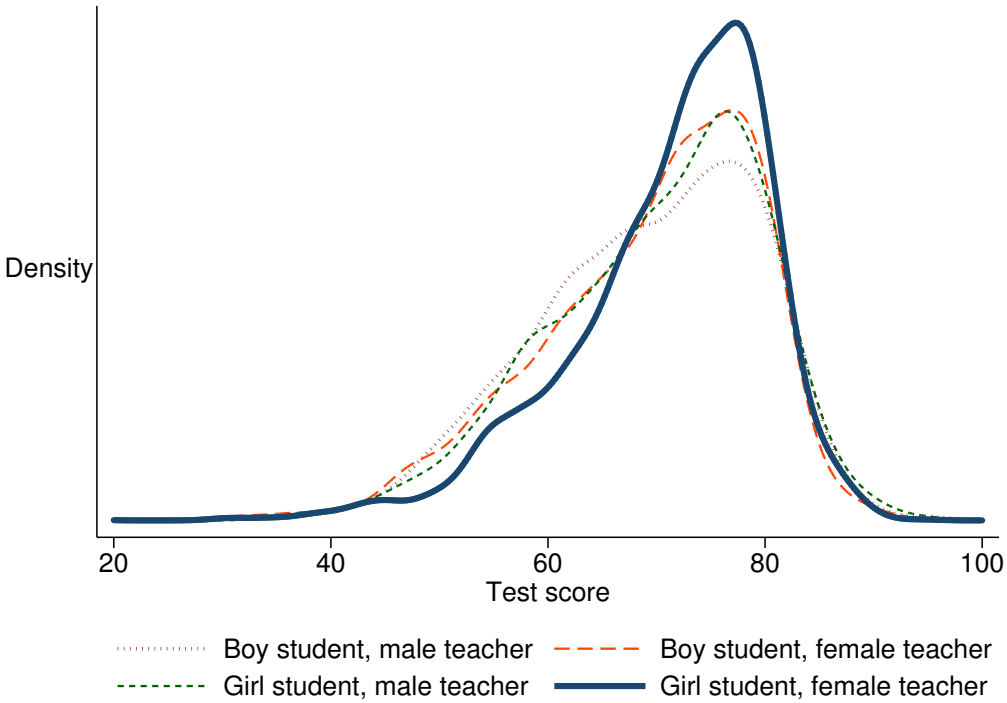
performance among the low perceived ability girls assigned to a female math teacher.

Prediction 3: $P(H|G^b, P^l, T^f) - P(H|G^b, P^l) < 0$, that is, being assigned a female math teacher will reduce low perceived ability boys' belief in their ability to productively invest in themselves. This is derived from the psychological concept of identity threat, which refers to the negative response (low performance, reduced effort) that occurs when members of a privileged group see a threat to the status quo (Scheepers and Ellemers, 2005). In our context, the existing stereotype posits that boys are better at learning math than girls. Low perceived ability boys, confronted with the dual threats of an increase in the difficulty of math when they enter middle school and the appearance of a female math teacher, may interpret these as signals that threaten their perception of the status quo that, as boys, they are better than girls in learning math.

Next, we examine two features of our data - the distribution of perceived ability by gender and the distribution of math test scores - as preliminary tests of our assumptions and our main prediction, respectively. Despite performing no worse on math tests than boys, girls are nearly 10 percentage points more likely to report that they find math at least somewhat difficult. Furthermore, girls to the left of the median math test score are 15 percentage points more likely than girls to the right of the median to believe that boys are better at math than girls (54% vs. 39%). We offer this as prima facie evidence that negative gender stereotypes affect girls in our data, particularly low perceived ability girls.

Next, in Figure 2, we show a kernel density plot of math test scores for the four different teacher-student gender pairings ($G^g : T^f$, $G^g : T^m$, $G^b : T^f$, and $G^b : T^m$). Girls assigned a female math teacher outperform all other pairings, but only in (roughly) the left half of the distribution. A Kolmogorov-Smirnov test rejects the equality of the $G^g : T^f$ distribution from the combined distribution of the test scores of students in other teacher-student gender pairings with a p-value of less than 0.001, and, as we will discuss further in Section 5, quantile regressions show substantial gains in the first through third deciles. As well as being in line with our main theoretical predictions, these results also suggest that we should look among students in the left tail of the ability distribution for the potential impacts of teacher-student gender match.

Figure 2: Distribution of math test scores by teacher-student gender pairing



Notes: This figure plots the distribution of students' scores on math midterm examinations by the four possible teacher-student gender pairings. The sample is restricted to the estimation sample as described in Section 4. A gaussian kernel was used to generate the density plots. A Kolmogorov-Smirnov test rejects equality of the distributions of test scores between two groups: girls paired with a female teacher and the combined distribution of students in all other teacher-student gender configurations. Test scores are standardized within each grade within a given school so that ten points is one standard deviation and the mean is 70.

3 Setting

China's 1986 compulsory education law mandated that all children receive nine years of free compulsory education, including six years of primary schooling (the first to sixth grades) and three years of middle school education (seventh to ninth grade). Until the late 1990s, primary school graduates were required to attend an entrance examination to be eligible to enter middle school (Lai et al., 2011; Carman and Zhang, 2012). At the turn of the millennium, middle schools were prohibited from selecting students based on academic merit and the middle school entrance examination was later cancelled. In the same spirit, tracking of students to different classes based on demonstrated ability or academic performance has been banned in middle schools since a subsequent compulsory education law was issued in 2006.

There are currently two permitted methods of assigning students to classes in China's middle schools: (1) purely random assignment and (2) assignment of students to maintain similar average levels of performance across classes, based either on students' academic performance on primary school graduation examinations or on diagnostic examinations arranged by the middle school. In the first system, primary school graduates are assigned to a neighborhood middle school according to local educational authorities' regulations, e.g., districting, and then they are randomly assigned to classes by lottery or another quasi-random method[4]. In the second system, students are assigned to classes by an algorithm which takes into account their academic performance at the beginning of the seventh grade and enforces a "balanced assignment" rule. This rule requires that the average quality of students be comparable across classes (Carman and Zhang, 2012).

To understand this second rule, consider the following example. Assume that one middle school has a total of 200 incoming seventh-grade students, who will be assigned to five classes. Students are first ranked by their total scores on primary school graduation examinations and then are assigned to classes according to their score ranks. For example, the top five and the bottom five students could be assigned to the five classes so that the best (ranked first) and the worst (ranked 200th) students are in the same class, the second best and the second worst are in the same class, and so on. That is, the average rank of students in each class - (1+200)/2 for class one, (2+199)/2 for class two, (3+198)/2 for class three, and so on - is kept about the same, in this case, 201/2.

In our empirical work, we will exploit these two methods of assigning students to classes as

[4]For instance, according to alphabetical order by surname, i.e., every n^{th} student assigned to the n^{th} class.

providing potentially quasi-random matching of student gender to teacher gender. This system is not implemented with perfect fidelity, however, particularly as students move beyond the first grade of middle school, i.e., from the seventh grade to the eighth and ninth. Unlike in many western countries, where admission to high school or university is either according to residence or based on multiple dimensions (e.g., grades and teacher recommendations), China's high school admissions system relies almost exclusively on entrance examinations (Zhang, 2016). Furthermore, the promotion of middle school administrators is largely determined by their school's students' performance in the high school entrance examination. More specifically, promotion is often awarded according to the annual number of graduates admitted to elite high schools. As a result, despite the banning of class tracking some middle schools assign students to classes based on their academic performance in order to better prepare top students for the entrance examination. Along with this sorting, school administrators may channel better teachers and more resources to classes with higher-ability students to maximize the chances that some of these students place in the best high schools.

This practice is more common in the eighth and ninth grades than in the seventh. This means that after their first semester or year of middle school, students may be reassigned to different classes based on their academic performance even if they are randomly assigned at the beginning of the seventh grade. In this analysis, as in Hu (2015), we restrict our attention to students randomly assigned to classes in the 7th grade and in those schools where random assignment of students to classes is maintained throughout middle school.

4 Data and empirical strategy

This section describes our data sources and empirical approach. Section 4.1 outlines the data we use and provides summary statistics. Section 4.2 describes the identification strategy we use, stating and testing our identifying assumptions.

4.1 Data sources

The main data source we use in this paper is the baseline wave[5] of the China Education Panel Survey (CEPS) conducted by the National Survey Research Center at Renmin University of China.

[5]At the time of writing, this is the only available wave of the study.

The CEPS is a nationally representative longitudinal survey that aims to track middle school students through their educational progress and later labor market activities. The baseline survey of the CEPS adopted a stratified, multistage sampling design with probability proportional to size, randomly selecting approximately 20,000 seventh and ninth grade students from 438 classes in 112 schools from 28 counties across mainland China during the 2013-2014 academic year. In each selected school, four classes were randomly chosen, two from the seventh grade and two from the ninth. All students in the selected classes were then surveyed. The CEPS uses five different questionnaires, administered to students, parents, homeroom (banzhuren) teachers, main subject (math, Chinese, and English) teachers, and school administrators, respectively. It is China's first nationally representative survey targeting middle school students, comparable to the Adolescent Health Longitudinal Studies (AddHealth) in the U.S. and the National Education Panel Survey (NEPS) in Europe.

The CEPS contains rich demographic data on students and their families, as well as detailed information on students' beliefs, aspirations, and time use. It also collects administrative school records on students' midterm test scores in the following three compulsory subjects: math, Chinese, and English. The scores are standardized in terms of school and grade, with a mean of 70 and a standard deviation of 10. These tests are graded by math teachers in the student's grade, and the grader may or may not be the student's own teacher. While this departs from the ideal scenario of blinded or third party grading, we argue in the footnote[6] that lack of blinding is unlikely to substantially bias the estimates we focus on.

The teacher questionnaire contains rich information on teacher characteristics, including teachers' age, gender, education levels, years of teaching experience, whether the teacher graduated from a university for teachers, whether the teacher holds a senior professional rank, and whether the teacher has won any teaching awards at various levels. The survey also contains information on the subject and the class the teacher taught during the 2013-2014 academic year. We limit most of our analyses to the matched math teacher-student dataset.

[6]First, midterm exams in mathematics use items that are mostly graded on objective criteria. These math tests thus allow less scope for score manipulation than do tests with greater use of items which necessitate subjective grading criteria, e.g., grades for essays in the language arts. Second, while teachers may display gender-specific discrimination in grading (Ehrenberg et al., 1995; Lavy, 2008; Fryer and Levitt, 2010), there is little available evidence showing test score manipulation based on teacher-student gender match. For example, both Dee et al. (2016) and Diamond and Persson (2016) find that student gender is not correlated with the extent of score manipulation. Even if teachers have an overall bias towards girls, as in Lavy and Sand (2015), this will be absorbed by the student gender dummy in the regressions as long as the discrimination does not vary with teacher-student gender match. Finally, we have even less reason to believe that any extant bias in grading will differentially affect the low performing students in a given gender.

The survey also collects data on the assignment mechanism used to assign students to classrooms, collected both from school principals and homeroom teachers[7]. The options are 1) tracking, 2) assignment according to students' household registration location, 3) either literally random assignment ("sui ji", meaning 'by chance') or according to the average-equilibrating algorithm described above, or 4) through other methods. About 85% of middle schools in our data assigned entering students to classes in either a random or an average-equalizing manner. Among those schools, one third reassigned students based on past academic performance when they entered the eighth or ninth grade. In our analysis, we will treat assignment to class as random for seventh graders in those schools reporting use of either purely random assignment or the average-equalization algorithm to assign seventh-grade students to classes, and for ninth graders in the subset of these schools which also report not reassigning eighth and ninth grade students to new classes in terms of previous academic performance. If this assumption is valid, our approach allows us to causally estimate the effect of teacher gender on student outcomes[8].

Table A.1 presents summary statistics for students by gender for those students randomly assigned to classrooms. The average age of girls is younger than for boys, and girls are more likely to have more educated parents and higher family incomes. Girls in our sample also have more siblings than boys, a consequence of the prevailing son-favoring tradition and the birth control policy in China, which allows for multiple children in some cases if the first child is a girl. Finally, girls perform better than boys on math tests administered in class.

Table A.2 shows summary statistics for teachers in the classrooms studied in Table A.1. In our data, 39% of the students are taught by male math teachers, alleviating the challenge faced in Antecol et al. (2015) where there was an insufficient number of male teachers to draw strong conclusions from some of the comparisons made. Female math teachers are on average younger and less experienced than their male counterparts. However, female teachers appear to be more qualified than their male counterparts in terms of education and proportion having won a teaching award at the province or national level[9].

[7]This data is self-reported. We argue that reporting bias in the assignment mechanism data is unlikely because the data collection process stresses the anonymity of the data (all identifying information is removed from the datasets released to scholars) and the data is collected by academics and graduate students, not government officials. We also limit the analysis to grades where both school principals and homeroom teachers report use of random assignment. Homeroom teachers are less likely than principals to face potential negative consequences of the school using a non-random assignment mechanism, and this restriction serves as a further check on the principal's self-report.

[8]This is assumption also investigated in Hu (2015).

[9]A teaching award at the national level is the most prestigious, followed by an award at the province level, and awards at the city level (the smallest of the three geographical units) are the least prestigious.

The significant differences in characteristics between girls and boys and between female and male math teachers above may reflect certain gender-specific patterns at the region or school level. For instance, girls and female teachers may be more likely to come from urban schools. In the next subsection, we show evidence that our empirical approach reduces the risk of potential bias stemming from such heterogeneity between teachers between schools. Specifically, our empirical strategy compares male and female teachers within a grade within a school. We show that these observed differences attenuate dramatically and cease to be significant at this level of comparison.

4.2 Empirical strategy

In this subsection we outline our empirical strategy. We first discuss our approach to estimating the effects of being assigned a female math teacher on female and on male students. We then test the identifying assumptions we must satisfy in order to interpret our coefficient estimates causally.

In this paper we exploit the random assignment of students to classrooms to estimate the impact of teacher-student gender match on students' beliefs, aspirations, investment behavior, and performance on in-school examinations. We estimate a reduced form regression equation, controlling for grade-by-school fixed effects and a vector of observable, predetermined characteristics at the child and teacher levels. Specifically, to determine whether teacher gender differentially affects the outcomes of interest for boys and girls, we estimate the following equation using CEPS data:

$$Y_{icgj} = \beta_0 + \beta_1 FS_{icgj} + \beta_2 FT_{cgj} + \beta_3 (FS_{icgj} * FT_{cgj}) + \gamma_0 LPA_{icgj} + \gamma_1 (LPA_{icgj} * FS_{icgj}) + \gamma_2 (LPA_{icgj} * FT_{cgj}) + \gamma_3 [LPA_{icgj} * (FS_{icgj} * FT_{cgj})] + \beta_4 SC_{icgj} + \beta_5 TC_{cgj} + \eta_{gj} + \epsilon_{icgj} \quad (3)$$

The variables are defined as follows. Y_{icgj} denotes the outcome of interest for student i in class c of grade g in school j. FS_{icgj} is an indicator equal to one if student i is female, and FT_{cgj} is also an indicator, equal to one if the teacher in class c in grade g of school j is female. LPA_{icgj} is an indicator equal to one if the student perceives herself to be of low ability. SC_{icgj} is a vector of predetermined characteristics at the student level, TC_{cgj} is a similar vector for teachers, η_{gj} is a grade-by-school fixed effect, and ϵ_{icgj} is a robust standard error, clustered at the school level[10] to allow for heteroskedasticity and arbitrary serial correlation across students within a given school. Unless otherwise specified, the controlled-for student-level characteristics determined prior

[10] All of our results continue to hold if we instead cluster at the (less conservative) classroom level.

to assignment of teacher gender include age, ethnicity (either Han or non-Han), hukou status (agricultural or not), parents' education levels, the child's number of siblings, and a categorical measure of household income (low income or not). The teacher-level predetermined characteristics include age, education level, years of work experience, whether the teacher graduated from a normal (i.e., teacher training) university, whether the teacher holds a senior rank, and whether she or he has won teaching awards at the city, province, or national level, respectively.

Intuitively, our estimation strategy compares the academic performance of students who study in the same grade in a middle school and share background characteristics, but are randomly assigned to either a female or male math teacher. Our identifying assumption is that, by virtue of random assignment, the match of FS_{icgs} to FT_{cgs} is orthogonal to predetermined characteristics which may influence beliefs, investment, or achievement. We test this assumption later in this section.

There are two parameters of central interest in this paper. The first is γ_3, which we interpret as a quasi-experimental estimate of the effect of assigning a female math teacher on low-perceived ability girls relative to the effect for low perceived ability boys. The second parameter is γ_2, which captures the effect on all low perceived ability students of being paired with a female teacher, using those assigned to a male teacher as the comparison. By virtue of the inclusion of γ_3, γ_2 is also the entire effect of being assigned a female math teacher on low perceived ability boys. Of ancillary interest is $\gamma_2+\gamma_3$, the total effect on girls of being assigned a female teacher relative to girls assigned a male teacher. If our assumption of orthogonality is satisfied, estimating Equation 3 using OLS should recover unbiased estimates of these parameters.

To test our assumption that within a grade within a given school, the match of student gender to teacher gender is randomly assigned, we follow Antecol et al. (2015), regressing math teacher gender on the same set of observable, predetermined student and family characteristics described above that we control for in our main empirical specification[11]. We conduct two regressions - one without any fixed effects, and a second with the grade-by-school fixed effects we use in our main empirical specification. For each regression we present coefficient estimates and report the F-statistic and p-value from a Wald Test of the joint significance of the regressors. We present these results in columns 1 and 2 of Table 1. With the inclusion of grade-by-school fixed effects, our F-test fails to reject the null that the regressors are together not significant predictors of teacher gen-

[11] This method is also discussed in Bruhn and McKenzie (2009) and Hansen and Bowers (2008).

der. This result supports our main identifying assumption that students' observable predetermined background characteristics are balanced along the gender of math teachers within the same grade in a given school. While we cannot rule out the possibility that in some cases influential parents or individuals successfully lobbied to be placed with a better teacher, we conclude from these results that such non-random matching of teachers to children is unlikely to be common enough to substantially bias our estimates. Nonetheless, this could exert an upward bias on the estimates we generate relative to what they would be in a context with perfect fidelity of implementation. As we rely on teachers' reports of whether they use tracking or random assignment, it may also be the case that some schools which report using random assignment in fact use tracking. Deliberate misreporting of tracking as "random" would bias upward our estimates of the effect of female teachers on the best students (i.e., the not low perceived ability) and bias downward the effect on worse students (more likely to be low perceived ability), who are less likely to be assigned to "good" teachers under a tracking system wherein the administrators are seeking to maximize the performance of the best students.

The CEPS asks students how difficult they found learning math in the sixth (and final) grade of primary school, and we use this question to classify students' perceived ability. Specifically, we classify those students who found learning math in the sixth grade to be "very difficult" as low perceived ability. We classify those who report sixth grade math to be "somewhat difficult," "not so difficult," or "easy" not to be of low perceived ability. In Table A.3 we show characteristics of students, by gender, for both of the perceived ability groups. Gaps between boys and girls described earlier persist across groups, though consistent with stereotypes, there are more girls in the low perceived ability group than in the not low perceived ability group.

It is important to note that this data is observed at the same time as all of the other data, specifically, after teacher assignment. It is possible, therefore, that teacher assignment may affect recall of perceived ability. To test for this possibility, we run the same regressions of teacher gender on predetermined characteristics, only restricting our analysis to low perceived ability students. We show our results in columns 3 and 4 of Table 1. The general pattern is the same as that for the entire sample - once we control for grade-by-school fixed effects, we fail to reject the null that these characteristics are jointly insignificant.

It is also possible that the determinants of perceived ability differ between boys and girls in a way that may predict their test scores. If this were true, it would influence our interpretation of γ_3.

Table 1: Test for randomization

	Full sample		*Low perceived ability*	
	(1)	(2)	(3)	(4)
Number of siblings	-0.021	-0.006	-0.026	0.001
	(0.016)	(0.006)	(0.025)	(0.013)
Household is poor	-0.053	0.005	-0.100**	0.014
	(0.033)	(0.013)	(0.046)	(0.026)
Female	0.000	0.003	-0.078**	-0.015
	(0.012)	(0.005)	(0.037)	(0.016)
Age	-0.040	-0.011**	-0.071***	-0.006
	(0.025)	(0.005)	(0.028)	(0.007)
Ethnic minority	-0.150*	0.013	-0.109	0.026
	(0.089)	(0.018)	(0.099)	(0.023)
Holds agricultural hukou	-0.057*	-0.010	-0.112*	-0.042
	(0.032)	(0.013)	(0.057)	(0.032)
Mother's education level				
Middle school	0.125***	0.009	0.140***	-0.008
	(0.031)	(0.013)	(0.046)	(0.022)
High/technical school	0.112***	0.003	0.115	0.043
	(0.035)	(0.013)	(0.074)	(0.038)
College or above	0.139***	0.005	0.066	-0.069
	(0.041)	(0.015)	(0.102)	(0.065)
Father's education level				
Middle school	0.038*	-0.010	0.065	-0.012
	(0.022)	(0.009)	(0.040)	(0.027)
High/technical school	0.022	0.000	0.018	-0.041
	(0.030)	(0.014)	(0.063)	(0.045)
College or above	0.051	0.010	0.267***	0.149***
	(0.036)	(0.017)	(0.075)	(0.061)
Low perceived ability in math	-0.058*	-0.015		
	(0.033)	(0.018)		
Grade-by-school fixed effects		X		X
Number of observations	8,294	8,294	850	850
R-squared	0.08	0.66	0.18	0.85
Joint test F-statistic	3.21	0.97	14.27	1.55
[p-value]	[0.00]	[0.48]	[0.00]	[0.12]

Notes: This table shows results from four separate regressions of math teacher gender (=1 if female) on the set of independent variables listed in the first column, following the test in Antecol et al. (2015). Columns 1 and 2 show estimates generated using the entire sample and columns 3 and 4 show estimates generated using the low perceived ability group only. * p<0.1, ** p<0.05, *** p<0.01.

To examine this possibility, we regress test scores on the vector of student-level predetermined characteristics and, using these coefficients, generate a predicted test score for each student. In Figure A.2, we plot these predicted test scores separately for boys and girls in each of the two perceived ability groups. These plots show no evidence of differences in the distribution of predicted test scores between genders in either group.

As a robustness check and further safeguard against possible omitted variables bias in the perceived ability measure, we also generate estimates from an alternative specification. In this specification, we estimate the effect of teacher-student gender match on our main outcome variables (perceived difficulty of current math class, aspirations, stereotypical beliefs, and math test scores) defining the low perceived ability group to be those whose math test score is below the median value of their teacher-gender pairing group (e.g., those boys paired with a male teacher whose test score is below the median score for that group) instead of using the self-reported data. The results, presented in a table and figure in the appendix, remain largely similar in magnitude and significance.

Another descriptive comparison of interest is teacher quality across genders. This paper aims to investigate the effect of female math teachers on student achievement. To ensure that we are isolating the effect of gender, we need to establish whether male and female teachers differ on observable characteristics, such as aptitude, which could drive any effects we measure (Cho, 2012; Antecol et al., 2015). Table A.4 reports the estimation results for conducting a similar empirical test to that in Table 1, only conducting the analysis at the teacher level. These predetermined characteristics include age, a dummy for having earned a full-time bachelor's degree or higher qualification, a dummy for having attended a normal university, years of teaching experience, and two dummies for winning teaching awards at different levels. After conditioning on grade-by-school fixed effects, we again fail to reject the null that within a grade within a school, these characteristics are not jointly predictive of the teacher's gender.

5 The effects of being assigned a female math teacher

In this section, we present results from applying our empirical strategy to the CEPS data. First, we estimate the impact of teacher-student gender match in mathematics on student beliefs and aspirations. We then look at how this match affects investment in human capital, followed by analysis

of its impact on performance on math tests.

5.1 Beliefs and aspirations

In this subsection, we conduct a test of the model's prediction that being assigned a female math teacher should positively affect beliefs and aspirations for low perceived ability girls. We investigate the impact of teacher gender on three belief variables: perceived difficulty of current math class, the careers to which students aspire, and anti-girl stereotypes. Our specification follows Equation 3, using grade-by-school fixed effects and the full battery of controls for students and teachers. We also control for students' math test scores, allowing us to compare changes in beliefs while controlling for performance.

For the analysis of perceived difficulty, we use the present-time analog to the baseline perceived ability question[12], students' response to the prompt "how difficult do you find your current math class to be?" Potential responses were as before ("very difficult," "somewhat difficult," "not so difficult," and "not difficult at all") and we code the variable as we do with perceived ability, as an indicator equal to one if the response is "very difficult." To study the impact of teacher-student gender match on aspirations, we use children's response to the prompt "what job would you most like to do when you grow up?" There are several possible responses to the question[13]; our theory predicts the clearest break between jobs in the language and visual arts (designer; artist/actor), which are traditionally more common jobs for women in China, and everything else. For stereotypes, we estimate the effect of teacher-student gender match on whether the student agrees with a statement that boys are better than girls at learning math.

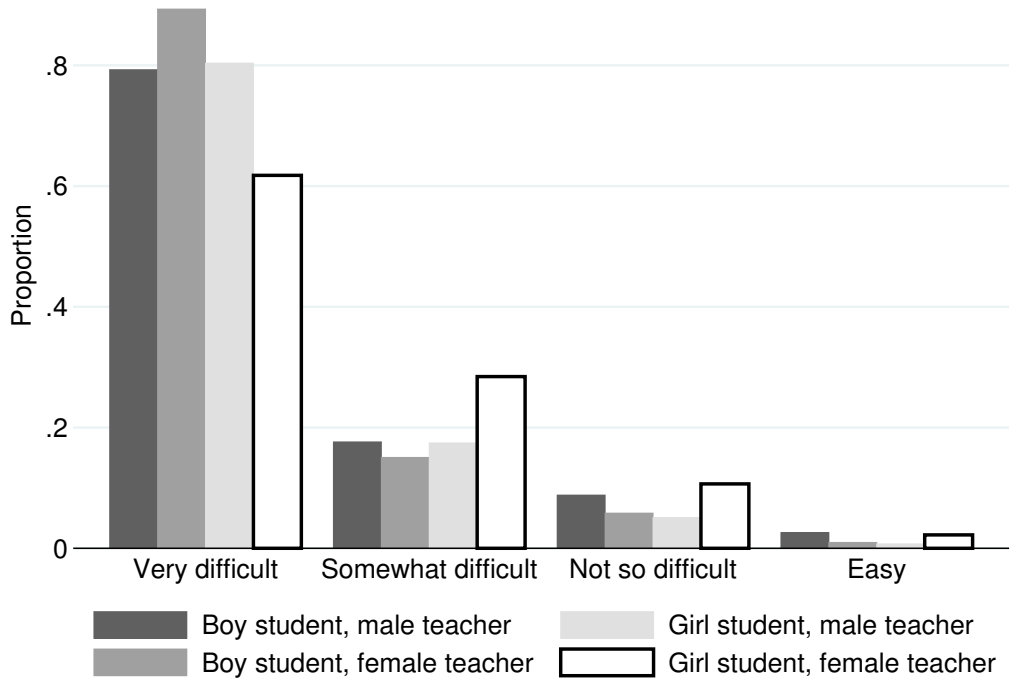
We present our results in Table 2. In column 1, our results suggest that being taught by a female math teacher reduces low perceived ability girls' probability of perceiving math as "very difficult" by 20 percentage points, and we see evidence that being assigned a female math teacher is also associated with an increase in low perceived ability boys' perceived difficulty of math. As predicted, while the estimated effect for not-low perceived ability girls assigned to a female teacher is the same sign as for the low perceived ability girls, it is an order of magnitude smaller and not statistically significant.

[12]Recall that the baseline perceived ability question asked about the child's experience in the sixth grade; this question refers to the child's current experience in either the seventh or ninth grade.

[13]The options are 1. Government Official, 2. Business manager, 3. Scientist/engineer, 4. Teacher/doctor/lawyer, 5. Designer, 6. Artist/actor, 7. Athlete, 8. Skilled worker, 9. Other, 10. Don't care, 11. Don't know.

We also present results for low perceived ability students visually in Figure 3. In this figure, we plot the distribution of perceived difficulty of the current math class for each possible teacher-student gender pairing, restricting the sample to low perceived ability children. This shows the same pattern as the coefficients - girls assigned to a female teacher are at least 20 percentage points less likely to perceive math to be very difficult than any other group, and boys assigned to female math teachers are at least 10 percentage points more likely to find math very difficult than any other group. In column 1 of Table A.5, we present this estimate using students below the within-group median test score instead of the low perceived ability group. We observe below-median girls assigned to a female teacher are 7.8 percentage points less likely to find math very difficult. While smaller than our coefficient for the low perceived ability group, this estimate retains both the predicted sign and statistical significance. Figure A.3 gives the below-median analog to Figure 3.

Figure 3: Low perceived ability students' current perception of the difficulty of math, by gender of student and math teacher



Notes: This figure plots the response of low perceived ability students to the prompt: "how difficult do you find your mathematics course at the moment?" This shows a clear rightward shift (towards lower perceived levels of difficulty in mathematics) for low perceived ability girls assigned to a female teacher, relative to all other teacher-student gender pairings.

Table 2: Effects on beliefs and aspirations

	(1) Current math class perceived as very difficult	(2) Aspires to jobs in art and design	(3) Holds anti-girl stereotypes
Girl x low perceived ability	0.046	0.105***	0.351***
	(0.042)	(0.034)	(0.053)
Female teacher x low perceived ability	0.100**	-0.031	0.079
	(0.046)	(0.034)	(0.058)
Girl x female teacher low perceived ability	-0.205***	-0.110**	-0.038
	(0.057)	(0.056)	(0.070)
Girl	0.051***	0.184***	-0.130***
	(0.013)	(0.017)	(0.030)
Female teacher	0.010	0.004	0.045
	(0.017)	(0.018)	(0.032)
Girl x female teacher	-0.037	0.008	-0.047
	(0.017)	(0.019)	(0.035)
Number of observations	8,276	8,213	8,117

Notes: The regression specification used is given in Equation 3, adding a control for the student's math test scores. Point estimates and their precision are largely unchanged by removing this final control. Robust standard errors clustered at the school level are shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

In column 2 of Table 2, we present estimates of the effect of being assigned a female math teacher on students' career aspirations. We estimate that for low perceived ability girls, being assigned a female math teacher is associated with an 11 percentage point decrease in aspiring to traditionally female jobs. The positive and significant coefficients on the "girl" and "girl x low perceived ability" variables corroborate our choice of variable coding - girls, and particularly low perceived ability girls, are more likely to aspire to these jobs, independent of the gender of their teacher. The effects of being assigned a female teacher on all other groups (low perceived ability boys, all other boys and girls) are at least an order of magnitude smaller and insignificant. In Table A.5 we see no effect on aspirations for the below-median girls assigned to female teachers.

In column 3, our estimate shows a small, insignificant effect on girls' stereotypical beliefs. The overall gender-specific effect ($\beta_3 + \gamma_3$, that is, the coefficient on girl x female teacher plus the coefficient on girl x female teacher x low perceived ability) however, is 8.5 percentage points, or 18.3% of the 46.5% of girls in our sample who hold these beliefs. In column 3 of Table A.5, we see a coefficient on girl x female teacher x below median of 8.0 percentage points, significant at the 10% level, and a total effect of 11.7 percentage points, or 25% of the baseline proportion. These results lead to two conjectures: one, that it may be harder to change global beliefs (stereotypes) than local beliefs (perceptions of own ability, as proxied by perceived difficulty); and two, that those with somewhat higher perceived ability may be more prone to updating their global beliefs when presented with a positive role model. In the context of our model, the mapping from a child's prior to the size of her update, as in Figure A.1, may be less right skewed for stereotypes than for perceived ability.

5.2 Investment in human capital

We next conduct a series of tests of the model's prediction that teacher-student gender match should positively change investment behavior for low perceived ability girls matched with female math teachers. We test this using four different dependent variables: students' reported enrollment in math tutoring, their total hours in tutoring (including, but not only, math tutoring), their hours spent on homework, and their enrollment in math olympiad tutoring. We give these results in Table 3.

Estimates presented in column 1 suggest that for low perceived ability girls, teacher-student gender match is associated with a 9.1 percentage point increase in enrollment in math tutoring.

Low perceived ability boys assigned to female teachers, on the other hand, spend substantially less time in tutoring than those assigned to male teachers. These estimates of γ_2 and γ_3 are also in line with our model's predictions. In Section 6, we explore the possible sources (i.e., parents, teachers, or children) of this change in investment. Also, and again as predicted, we see a much smaller and statistically insignificant estimate of the girl x female teacher coefficient.

In columns 2 and 3, we present estimates of the effect of teacher-student gender match on time-use data, first for weekly hours spent in tutoring, then for hours per week spent on homework. The pattern of estimates in column 2 is similar to that in column 1 - when assigned to a female math teacher, low perceived ability girls spend more time in tutoring (three hours per week), and low perceived ability boys spend slightly less (1.5 hours). These results are only suggestive, however, as the time use data is not specifically about math tutoring, but rather time spent in tutoring overall. In column 3, we see no significant effect on hours spent on homework for either group.

In column 4, we estimate the effect of being assigned a female math teacher on enrollment in math olympiad tutoring. This tutoring is designed for students who aim to develop advanced math skills. Since the low perceived ability girls also have lower math test scores than their peers, it is unlikely that the differences in beliefs apparently induced by a female math teacher would lead to substantial gains in olympiad tutoring, which is targeted at students of relatively higher ability. On the other hand, if role models also affect beliefs and behavior at the higher end of the perceived ability spectrum, we may find an impact on olympiad tutoring for higher perceived ability girls. In line with what our model predicts, we see no significant effect of being assigned a female math teacher on enrollment in math olympiad tutoring among girls at any perceived ability level. Finally, consistent with the posited negative influence of anti-girl stereotypes in math, girls in our sample are 30% (1.8 percentage points) less likely to enroll in math olympiad tutoring than boys despite girls' superior performance on mathematics examinations. We explore this gap in test scores further in the next section.

5.3 Academic performance

In this subsection we examine the effect of teacher-student gender match on students' performance in mathematics. Here we focus on children's scores on midterm math examinations to quantify the differences apparent in Figure 2. We present these results in Table 4. The first column shows the

Table 3: Effects on investment in human capital

	(1) Enrolled in math tutoring	(2) Hours in tutoring	(3) Hours spent on homework	(4) Math olympiad tutoring
Girl x low perceived ability	-0.054	-2.203***	-1.044	-0.001
	(0.035)	(0.933)	(1.252)	(0.018)
Female teacher	-0.082**	-1.548	0.687	-0.014
x low perceived ability	(0.036)	(0.996)	(1.353)	(0.022)
Girl x female teacher	0.091*	3.057***	0.392	0.000
x low perceived ability	(0.052)	(1.253)	(1.595)	(0.024)
Girl	0.022	0.080	0.716*	-0.018**
	(0.016)	(0.295)	(0.403)	(0.008)
Female teacher	-0.012	-0.262	0.095	0.018
	(0.023)	(0.403)	(0.467)	(0.016)
Girl x female teacher	0.027	0.262	0.516	-0.006
	(0.019)	(0.363)	(0.519)	(0.011)
Number of observations	8,257	8,019	7,995	8,257

Notes: The regression specification used here is given in Equation 3. The dependent variable is given in the column headings. Robust standard errors clustered at the school level are shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Effects on math test score

	(1)	(2)
Girl x low perceived ability	-0.414	-0.193
	(1.267)	(1.248)
Female teacher	-2.294*	-1.472
x low perceived ability	(1.240)	(1.288)
Girl x female teacher	4.783***	4.459***
x low perceived ability	(1.621)	(1.657)
Girl	1.191***	1.250***
	(0.482)	(0.492)
Female teacher	0.406	1.849***
	(0.423)	(0.684)
Girl x female teacher	0.187	0.068
	(0.535)	(0.541)
Number of observations	8,294	8,294
Grade-by-school fixed effects		X

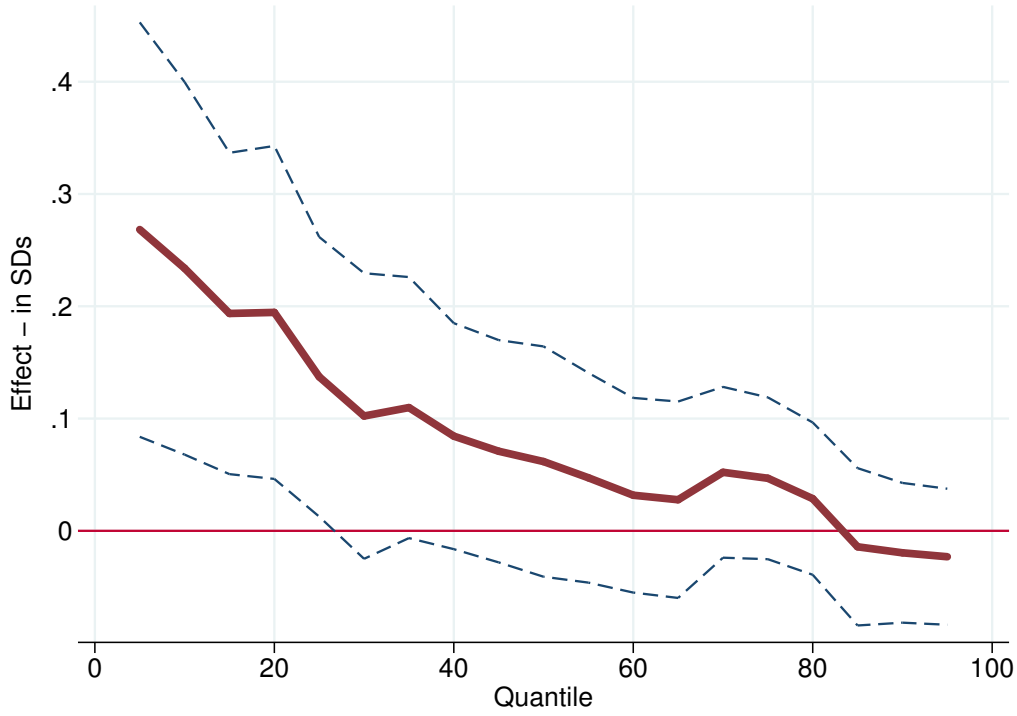
Notes: The dependent variable is the student's math test score. Robust standard errors clustered at the school level are shown in parentheses, and the coefficients are estimated using the specification in Equation 3. * p<0.1, ** p<0.05, *** p<0.01.

estimates with no fixed effects and the second column shows estimates generated with grade-by-school fixed effects (the specification used Tables 2 and 3).

We find that having a female math teacher increases the math test scores of low perceived ability girls by 4.5 points, or 0.45 sample standard deviations (SDs), controlling for other characteristics as in Equation 3. In line with the predictions of the model, girls who do not perceive themselves of low ability appear to gain no gender-specific benefit from being assigned a female teacher ($\beta_3 = 0.068$, $\sigma = 0.541$). Consistent with the patterns shown in the previous subsections, we also see some evidence that low perceived ability boys' test scores decline, though the effect is not significant and is much smaller than the effect for low perceived ability girls.

We present quantile regression results in Figure 4. To generate this figure, we estimated equation 3 without any of the low perceived ability independent variables and recovered coefficient es-

Figure 4: Quantile regression results for math test scores



Note: This figure presents coefficient estimates and standard errors of β_3 estimated using Equation 3, removing the low perceived ability controls and their interactions, at 19 quantiles (spanning from the fifth to 95th centile at five-centile increments) with midterm math test score as the dependent variable.

timates of β_3 and the corresponding confidence interval at every fifth centile between the fifth and 95th. The pattern that we see in Table 4 and in Figure 2 also appears in Figure 4 - the largest gains from teacher-student gender match accrue to those girls in the left half of the distribution, specifically the first quartile. In column 4 of Table A.5, we estimate a positive effect of teacher-student gender match on math test scores for the below-median group of girls assigned to female math teachers. These results are substantially smaller than our estimates generated using perceived ability (around 0.11 SDs for the below-median group, as opposed to the 0.45 SD gain we measure for the low perceived ability group) and for the left quartile of the distribution in the quantile regressions (0.2-0.3 SD). This discrepancy is also in line with our model's predictions. While the below-median and quartile results are both sizable, the framework in Section 2 predicts that it is specifically among the low perceived ability girls, not just the low performers, that we should see

the largest difference.

Other work on teacher-student gender match has found smaller effects on test scores, usually between 0.02 and 0.2 SD increases for girls assigned to female teachers (e.g., Paredes 2014; Lim and Meer Forthcoming; Muralidharan and Sheth 2016). Our estimate of β_3 generated using the entire sample (and dropping the independent variables related to low perceived ability) falls well within this range (0.09 SD), but our estimates of γ_3, i.e., for the low perceived ability girls, are substantially higher. There are two likely contributors to this divergence. The first is that, unlike other studies, we focus on a subgroup of interest for whom a simple model of investment in human capital under uncertainty predicts particularly large benefits from teacher-student gender match in math. The second is that estimates generated from samples without random assignment may not eliminate omitted variables bias from some unobserved characteristic or behavior driving some of the sorting of student gender to teacher gender (Rothstein, 2010). In Appendix C, we test the second hypothesis by comparing our main parameter of interest, β_3, estimated using the sample with random assignment, to estimates generated using the subset of schools and grades in our data who report nonrandom student assignment. Estimates generated using the sample of schools with non-random assignment are between 10 and 30% smaller than our overall estimates. While these results are not causal (we do not have random assignment of the student assignment mechanism), they are consistent with patterns seen in other papers studying the effects of teacher-student gender match, some of which use settings with random assignment, others of which do not (Dee, 2007; Paredes, 2014; Muralidharan and Sheth, 2016). The result is intuitive if two conditions hold: one, the largest benefits from teacher-student gender match indeed accrue, as we observe, to low perceived ability students, and two, schools which don't use a quasi-random method to assign students to classes are more likely to use tracking. As discussed in Section 4.2, this would mean that the best students are assigned to the best teachers, and the low perceived ability group - those most likely to benefit from being matched with a same-gendered math teacher - have a higher probability of being assigned to worse teachers.

6 Mechanisms and discussion

In this section, we first conduct a series of analyses to test for evidence of two potential drivers of the patterns we observe in the previous section - the first, described in our conceptual framework,

is that same-gendered math teachers serve as role models who counter the negative effects of stereotypes on student beliefs; the second is that there is some other characteristic of female teachers or their conduct which drives these results. We then provide a discussion of the main limitations of our analysis.

6.1 Mechanisms

In this subsection we first show that additional exposure to female role models in mathematics has additional positive effects on the outcomes we study. We then perform a series of analyses looking for evidence that the effects we observe in the previous section are driven by either teacher-specific characteristics or teacher conduct instead of by the effect of the teacher serving as a role model. We test for the following possibilities: one, that female math teachers lavish more attention on low perceived ability girls than do male teachers; two, that female math teachers are merely better teachers and it is these skill differentials which drive the observed effects; three, that female teachers exerting more effort than male teachers drives the effects; and four, that our findings are driven by differences in teaching methods between female and male teachers.

We first show that additional exposure to the role model increases the impact of teacher-student gender match on the outcomes we measure. We exploit the fact that some students' math teacher is also their homeroom teacher, and these students spend additional time each day in the presence of that teacher. This provides variation in the amount of students' exposure to the role model. Our framework predicts that this additional exposure should generate additional positive effects, and we test this by estimating the effect of a student being assigned a female math teacher who is also the student's homeroom teacher on beliefs, stereotypes, enrollment in math tutoring, and performance on the midterm math exam. We present these results in Table A.6. While the results are imprecise, the coefficients are large and for all but the tutoring variable, in the predicted direction.

Next, we present results from a series of tests that consider alternative explanations for the patterns we observe in Section 5. We test four possibilities: one, that female math teachers may choose to engage more with low perceived ability girls than do male math teachers; two, that female math teachers may simply be better at teaching those of low perceived ability than male teachers; three, that it is differential teacher effort instead which drives the results we observe; and four, that female teachers teach differently than do male teachers, and this difference is responsible for the

salutary effects of teacher-student gender match that we measure.

First we test for the possibility that teachers differentially engage students based on whether the teacher and student are of the same gender, i.e., that female teachers favor girls with more praise and attention, and vice versa. (Beaman et al., 2009; Hoffmann and Oreopoulos, 2009; Jones and Wheatley, 1990). The CEPS collects two key data points on classroom interactions between teachers and students: one, students' recall of whether their current math teacher frequently asks them questions, and two, whether the teacher frequently praises them in the classroom. Responses are coded on a four-point scale, ranging from one for "strongly disagree" to four for "strongly agree." We break this into a binary variable, mapping strongly agree and somewhat agree to one, and somewhat disagree and strongly disagree to zero. The results we show are not sensitive to recoding the middle values in either direction. In Table 5 we present our estimates from estimating Equation 3 using these two measures as outcome variables. Our results show that while female teachers are slightly more likely to ask students questions than male teachers, there is no evidence that female teachers favor low perceived ability girls either with more opportunities to respond to questions or more praise.

The second possibility is that female teachers are simply better teachers, and it is teaching skill that drives the gains we observe for girls with low perceived ability. To test for this, we generate two sets of results. First, we replace the teacher-student gender match variable (i.e., girl x female math teacher) in our estimating equation with an interaction term for girl x math teacher who won an award. We show these results in Table A.7. These results do not show no evidence of "better" teachers having an positive effect on perceived difficulty, aspirations, or performance of low perceived ability girls, though they appear affect stereotypical beliefs. To probe this further, we also conduct a horse race, reverting to the original specification in Equation 3 and adding the interaction variable for each of these qualifications (one interaction per regression) with the teacher-student gender match dummy. For each of the three regressions we run - interacting female math teacher with the math teacher's years of experience, whether she holds a degree from a normal university, and whether she received a teaching award at the provincial or national level, respectively - we find the interaction term is negative and insignificant, while γ_3 is of similar magnitude (0.3 SD or larger) and retains its statistical significance[14].

Next, we investigate the possibility that teacher effort drives these effects. The CEPS collects

[14] Results in tabular form are available from the authors but not included in this manuscript.

Table 5: Robustness checks - teacher attention and skill

	(1) Is called on frequently in math class	(2) Is praised frequently in math class
Girl	0.012	0.022
x low perceived ability	(0.053)	(0.048)
Female teacher	-0.084	-0.022
x low perceived ability	(0.055)	(0.043)
Girl x female teacher	0.035	-0.083
x low perceived ability	(0.080)	(0.069)
Girl	-0.030	-0.055
	(0.022)	(0.020)
Female teacher	0.057	0.024
	(0.035)	(0.036)
Girl x female teacher	0.008	0.030
	(0.025)	(0.024)
Number of observations	8,237	8,246

Notes: The regression specification used here is given in Equation 3, again with the addition of the midterm math test score. For Panel A, the dependent variable is the response, on a four point scale from one, strongly disagree, to four, strongly agree, to the prompt "the teacher calls on me frequently." Panel B's dependent variable, on the same scale, is the response to the prompt "the teacher often praises me." Robust standard errors clustered at the school level are shown in parentheses. All regressions control for the student's math test scores, but the point estimates and their precision are largely unchanged by removing this control. * p<0.1, ** p<0.05, *** p<0.01.

self reported time use data from teachers. We use the following data points: first, how many hours teachers spend preparing for class and grading homework, respectively. We use these as proxies for how much "effort" the teacher chooses to expend. Second, how many hours the teacher spends lecturing. We use this as a scale variable - schools determine how many classes the teacher is responsible for, which is the denominator by which we scale the effort variable. We generate three measures of effort: one, [hours in preparation: hours in class]; two, [hours grading: hours in class]; and three, [(hours in preparation + hours grading): hours in class]. In Tables A.8, A.9, and A.10, we estimate the effect of these ratios on perceived difficulty of math, whether the child holds anti-girl stereotypes, enrollment in math tutoring, and on the math midterm exam score. For none of these analyses do we observe a significant effect of teacher effort on outcomes for low perceived ability girls.

Finally, we look at the impact of teachers' use of different methods of teaching and their effect on low perceived ability girls. This tests for the possibility that the effects we observe are driven merely by female teachers employing different methods (e.g., engaging with students in a different way) rather than the role model effect. The CEPS records teachers' response to the following question - "how often do you use [TEACHING METHOD]: never, sometimes, often, or always?" - for each of three methods - "lecturing," "small group discussion," and "interactive discussion between teacher and students." The latter two options involve more interaction between the student and teacher and so we expect a priori for them to have a larger effect on the low performing girls if teaching method does in fact drive the results in Section 5. As with the student engagement variables, there are four possible responses for how often teachers use these methods - never, sometimes, often, and always. We code these as a binary variable, with often and always mapping to one and the other responses to zero. Table A.11 shows estimates of the effect of teachers' use of these methods on perceived difficulty of math and midterm math test scores. We see no positive effect of using either method on low perceived ability girls' outcomes.

6.2 Limitations

In this subsection, we outline a few limitations of our analysis, focusing on areas of departure from the ideal scenario in which to test our main hypotheses. Our first and main weakness is the lack of multiple time periods. In an ideal world, we would observe children's performance in

primary school, then observe their beliefs when they are paired with their teacher and estimate those effects, then observe investment decisions and, finally, observe performance. Instead, we observe a series of demographic characteristics and data collected in one period in the student's first year of middle school. It is possible, therefore, that the arrow of causality goes the other way, from some unobserved factor that boosts performance for these girls, which in turn changes perceived difficulty, investment, and aspirations. While possible, it would have to be the case that this unobserved factor accrues only to low perceived ability girls in math classes. In the previous subsection we presented a series of results suggesting that neither teacher aptitude nor any of a battery of teacher behaviors are likely to be the source of such reverse causality.

The second weakness is the use of the self-reported perceived ability measure. In an ideal setting we would observe children's actual performance in the sixth grade, and use this as a stratifying variable. While we have shown no evidence of difference in observable characteristics associated with this variable that would suggest omitted variables bias, we cannot conclusively exclude the possibility of some unobserved factor which affects both propensity to report low perceived ability and our main outcome variables. Nonetheless, the fact that we see similar patterns in perceived difficulty of math and math performance for both the below-median group and the low perceived ability group suggests that our conceptual framework's main predictions on the signs of our estimates appear to be borne out.

This study looks at the effects of teacher-student gender match in mathematics, a subject where girls face longstanding stereotypes against their ability. A good ancillary test of our theory would be to test for effects of teacher-student gender match on beliefs and test performance in subjects without stereotypes, namely, in English and Chinese. While we have information on teachers in these subjects, the very small number of male English or Chinese teachers in our data prevents us from using our identification strategy, which clusters at the grade-by-school level, to test for such effects.

Finally, we observe a change in children's enrollment in tutoring which admits several possible explanations. One possible explanation at odds with our interpretation of the results is that parents' and/or teachers' compensatory actions, including but not limited to enrolling low perceived ability children in more tutoring, causes the change in beliefs, aspirations, and performance we observe. While we do not deny the possibility that this may play some role for some students, the patterns in our empirical results and a few facts about the Chinese context suggest this is simi-

larly unlikely to be the most important driver of our empirical results. First, our analyses of teacher effort and interaction with students by gender show no evidence of differential teacher attention or effort driving the differences we observe. Second, were compensatory behavior by parents to drive this pattern, it would have to be the case that parents of boys assigned to female teachers respond by withdrawing their children from tutoring while the parents of girls assigned to female teachers respond by increasing enrollment in tutoring. Our explanation - these results come from a difference in enthusiasm, effort, and belief in oneself generated by the role model effect of being assigned a same-gendered teacher - is rooted in existing empirical and theoretical evidence from both economics and psychology (e.g., Bettinger and Long, 2005; Nixon and Robinson, 1999; Paredes, 2014; Lybbert and Wydick, 2016b; Bian et al., 2017). We argue that this explanation is more plausible and less of a "just-so" story than subgroup-specific compensatory action by the parents of low perceived perceived ability girls and boys assigned to female teachers. Lastly, we study a context where children are often actively involved in their education, particularly in the age range we study. Children in the CEPS are in middle school when our data is collected. Loyalka et al. (2013) find that an information intervention providing students in a different set of Chinese middle schools with estimated labor market returns to different levels of education affected these students' propensity to drop out of middle school. This evidence is consistent with the notion that children in Chinese middle schools make at least some of their own educational decisions.

7 Conclusion

In this paper, we study the potential for a role model to counter the effects of negative stereotypes. We examine a context with strong negative stereotypes regarding girls' math ability vis-a-vis boys' and find that being assigned a female math teacher confers a series of positive effects on low perceived ability girls. Teacher-student gender match is associated with a reduction in the perceived difficulty of mathematics, a change in aspirations, and an increase in both investment in human capital and in performance on math tests for low perceived ability girls. These results are consistent with the often-conjectured causal pathway that we formalize in Section 2 - that having a female math teacher provides a plausible role model for low perceived ability girls and this has a protective effect against the negative impact stereotypes can have on the formation of these girls' beliefs, aspirations, and academic outcomes.

This paper adds to a growing body of research (e.g., Bernard et al., 2014; Lusher et al., 2015; Lybbert and Wydick, 2016b; Genicot and Ray, 2017) in economics studying how information affects aspirations, educational decisions and outcomes. Together, this work shows that the informational environment a child faces and, specifically, the presence of a plausible example of success, may be a key lever for changing beliefs, increasing effort, and improving performance in school. More broadly, our work suggests that role models and the information they provide are likely an important input into the production of human capital, particularly among girls and other groups who for various historical or socioeconomic reasons may lack for a credible example of successful investment in certain types of human capital.

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Appendix

Appendix A: Appendix tables

Table A.1: Summary statistics for students

	(1) All	(2) Female	(3) Male	(4) Difference
Female (%)	48.71	-	-	-
Age	13.22	13.16	13.27	-0.10***
Minority (%)	11.31	11.78	10.86	0.92
Agricultural hukou (%)	48.44	47.55	49.28	-1.72
Father's years of education	10.69	10.75	10.62	0.13*
Father's highest level of schooling (%)				
Primary or below	13.77	13.46	14.07	-0.61
Middle school	41.14	40.93	41.33	-0.4
High school/technical school	25.43	25.04	25.79	-0.75
College or above	19.66	20.57	18.81	1.76**
Mother's years of education	9.97	10.08	9.87	0.20**
Mother's highest level of schooling (%)				
Primary or below	22.1	20.34	23.76	-3.42***
Middle school	38.11	39.7	36.59	3.12***
High school/technical school	22.92	22.58	23.25	-0.66
College or above	16.87	17.37	16.4	0.97
Number of siblings	0.69	0.75	0.64	0.11***
Household income "low"	18.11	16.97	19.18	-2.21***
Math test score	70.25	70.94	69.59	1.35***
Number of observations	8,345	4,065	4,280	-

Notes: Column 4 shows the gender differences in student characteristics with t-test results.
* p<0.1, ** p<0.05, *** p<0.01.

Table A.2: Summary statistics for teachers

	(1) All	(2) Female	(3) Male	(4) Difference
Female (%)	61.35	-	-	-
Age	37.94	36.95	39.5	-2.55**
Education level (%)				
Associate college or below	12.56	7.87	20	-12.13**
Part-time four-year university	34.78	33.07	37.5	-4.43
Full-time four-year university	48.79	54.33	40	14.33**
Master's degree or higher	3.86	4.72	2.5	2.22
Attended a normal university (%)	94.2	92.13	97.5	-5.37
Years of teaching experience	16.8	15.72	18.53	-2.81**
Holds a senior professional rank (%)	23.67	24.41	22.5	1.91
Won teaching award (%)				
At the province or national level	14.01	14.96	12.5	2.46
At the city level	43.96	42.52	46.25	-3.73
Observations	207	127	80	-

Notes: This table compares observable teacher characteristics across teacher gender. Column 4 shows the gender differences in teacher characteristics with t-test results. * p<0.1, ** p<0.05, *** p<0.01.

Table A.3: Background characteristics, summarized by gender and perceived ability

	Perceived ability			
	Low		*Not low*	
	(1) Girls	(2) Boys	(3) Girls	(4) Boys
Age	13.50	13.52	13.13	13.26
Ethnic minority	0.23	0.19	0.11	0.10
Holds agricultural hukou	0.56	0.64	0.47	0.49
Number of siblings	1.06	0.93	0.72	0.63
Low household income / poor	0.30	0.30	0.16	0.19
Father's years of schooling	9.47	9.30	10.86	10.68
Mother's years of schooling	8.41	8.41	10.21	9.92
Number of observations	536	471	3,934	4,351

Notes: this table shows group-specific means for the low perceived ability girls and boys in our sample and for those who are not low perceived ability.

Table A.4: Tests for gender-specific teacher quality

	(1)	(2)
Age	-0.010	-0.018
	0.009	0.030
Has B.A.	0.122	0.055
	0.078	0.249
Went to teachers' college	-0.242*	-0.222
	0.131	0.216
Years of experience	0.001	0.015
	0.008	0.027
Won award at province level	0.099	0.161
	0.115	0.387
Won award at city level	-0.027	-0.108
	0.073	0.255
Grade-by-school fixed effects		X
Number of observations	207	207
R-squared	0.06	0.70
Joint test F-statistic	2.31	0.25
[p-value]	[0.04]	[0.96]

Notes: This table shows coefficient and standard error estimates from regressing teacher gender on the predetermined teachers characteristics listed in the first column and conducting a Wald Test for their joint significance, similar to the results shown in Table 1 for student characteristics.

Table A.5: Replicating main results, using below median test score instead of perceived ability

	(1) Perceived difficulty of current math class	(2) Aspires to jobs in art and design	(3) Believes boys are better than girls at learning math	(4) Midterm math test score
Girl x below median	0.068***	0.026	0.287***	0.558
	(0.022)	(0.026)	(0.034)	(0.462)
Female teacher	0.007	-0.004	0.045	0.873***
x below median	(0.024)	(0.019)	(0.034)	(0.334)
Girl x female teacher	-0.078***	0.009	-0.080*	1.111*
x below median	(0.027)	(0.034)	(0.046)	(0.569)
Girl	0.058***	0.188***	-0.224***	0.468**
	(0.014)	(0.019)	(0.034)	(0.236)
Female teacher	0.026	0.006	0.036	0.607**
	(0.020)	(0.018)	(0.039)	(0.303)
Girl x female teacher	-0.039**	-0.013	-0.028	0.116
	(0.017)	(0.022)	(0.041)	(0.289)
Number of observations	8,300	8,251	8,151	8,345

Notes: The dependent variable in question is given in the column heading. Robust standard errors clustered at the school level are shown in parentheses, and the coefficients are estimated using the specification in Equation 3. * p<0.1, ** p<0.05, *** p<0.01.

Table A.6: Effect of having math teacher as homeroom teacher

	(1) Perceived difficulty of current math class	(2) Believes boys are better than girls at learning math	(3) Enrolled in after-school math tutoring	(4) Midterm math test score
Homeroom teacher = math teacher (HRMT) x LPA)	-0.033	-0.100	-0.068	-1.889
	(0.083)	(0.108)	(0.050)	(1.805)
HRMT x LPA	0.010	-0.003	0.169**	-1.863
	(0.102)	(0.132)	(0.078)	(2.582)
HRMT x LPA x girl	0.073	0.157	0.042	0.949
	(0.082)	(0.109)	(0.081)	(2.286)
HRMT x female teacher x girl x LPA	-0.113	-0.284**	-0.187	1.455
	(0.128)	(0.131)	(0.121)	(3.564)
HRMT	0.008	0.022	0.041	-0.885
	(0.031)	(0.054)	(0.037)	(1.116)
HRMT x female teacher	-0.084**	0.068	-0.048	3.468**
	(0.042)	(0.072)	(0.056)	(1.559)
HRMT x girl	-0.022	-0.087	0.014	-0.351
	(0.026)	(0.060)	(0.036)	(0.959)
HRMT x female x girl	0.027	0.053	-0.036	-0.166
	(0.034)	(0.078)	(0.047)	(1.117)
Number of observations	8,276	8,117	8,257	8,294

Notes: The dependent variable in question is given in the column heading. Robust standard errors clustered at the school level are shown in parentheses, and the coefficients are estimated using the specification in Equation 3. * p<0.1, ** p<0.05, *** p<0.01.

Table A.7: Teacher aptitude

	(1) Perceived difficulty of current math class	(2) Aspires to jobs in art and design	(3) Believes boys are better than girls at learning math	(4) Midterm math test score
Girl	-0.036	0.052*	0.359***	2.098**
x low perceived ability	(0.037)	(0.029)	(0.042)	(0.988)
Award-winning teacher	0.030	0.046	0.073	2.267*
x low perceived ability	(0.072)	(0.067)	(0.071)	(1.260)
Girl x award-winning teacher	-0.118	0.007	-0.194***	-1.174
x low perceived ability	(0.101)	(0.123)	(0.080)	(1.543)
Girl	0.031***	0.196***	-0.161***	1.275***
	(0.008)	(0.011)	(0.021)	(0.321)
Award-winning teacher	0.022	0.062**	-0.036	-0.301
	(0.025)	(0.029)	(0.041)	(0.952)
Low perceived ability	0.498***	-0.027	-0.163***	-9.143***
	(0.028)	(0.021)	(0.031)	(0.743)
Girl x award-winning teacher	-0.020	-0.039**	0.010	0.184
	(0.021)	(0.020)	(0.051)	(0.664)
Number of observations	8,276	8,213	8,117	8,294

Notes: The dependent variable in question is given in the column heading. Robust standard errors clustered at the school level are shown in parentheses, and the coefficients are estimated using the specification in Equation 3. * p<0.1, ** p<0.05, *** p<0.01.

Table A.8: Teacher effort 1

	(1) Perceived difficulty of current math class	(2) Believes boys are better than girls at learning math	(3) Enrolled in after-school math tutoring	(4) Midterm math test score
Girl x LPA	-0.093	0.406***	-0.030	2.826
	(0.073)	(0.058)	(0.055)	(1.775)
Hours prep: hours in class x LPA	-0.018	0.032	-0.006	1.516**
	(0.032)	(0.034)	(0.024)	(0.759)
Hours prep: hours in class x LPA x girl	0.037	-0.068*	0.021	-0.617
	(0.056)	(0.039)	(0.033)	(1.229)
Girl	0.036***	-0.161***	0.051***	0.748
	(0.011)	(0.026)	(0.018)	(0.485)
LPA	0.019*	0.001	-0.033***	-0.972*
	(0.011)	(0.020)	(0.010)	(0.583)
Hours prep: hours in class	0.520***	-0.192***	0.003	-10.552***
	(0.046)	(0.042)	(0.031)	(1.082)
Hours prep: hours in class x girl	0.520***	-0.192***	0.003	-10.552***
	(0.046)	(0.042)	(0.031)	(1.082)
Number of observations	8,212	8,055	8,193	8,230

Notes: The dependent variable in question is given in the column heading. Robust standard errors clustered at the school level are shown in parentheses, and the coefficients are estimated using the specification in Equation 3. * p<0.1, ** p<0.05, *** p<0.01.

Table A.9: Teacher effort 2

	(1) Perceived difficulty of current math class	(2) Believes boys are better than girls at learning math	(3) Enrolled in after-school math tutoring	(4) Midterm math test score
Girl x LPA	-0.071	0.357***	-0.031	3.192*
	(0.064)	(0.063)	(0.055)	(1.858)
Hours grading: hours in class x LPA	-0.053	0.015	0.000	1.488*
	(0.036)	(0.034)	(0.030)	(0.872)
Hours grading: hours in class x LPA x girl	0.013	-0.024	0.022	-0.990
	(0.042)	(0.041)	(0.050)	(1.299)
Girl	0.041***	-0.145***	0.034**	0.751*
	(0.011)	(0.029)	(0.017)	(0.451)
LPA	0.014	0.059***	-0.004	0.752
	(0.013)	(0.025)	(0.016)	(0.565)
Hours grading: hours in class	0.559***	-0.171***	-0.004	-10.498***
	(0.051)	(0.045)	(0.034)	(1.222)
Hours grading: hours in class x girl	0.559***	-0.171***	-0.004	-10.498***
	(0.051)	(0.045)	(0.034)	(1.222)
Number of observations	8,212	8,055	8,193	8,230

Notes: The dependent variable in question is given in the column heading. Robust standard errors clustered at the school level are shown in parentheses, and the coefficients are estimated using the specification in Equation 3. * p<0.1, ** p<0.05, *** p<0.01.

Table A.10: Teacher effort 3

	(1) Perceived difficulty of current math class	(2) Believes boys are better than girls at learning math	(3) Enrolled in after-school math tutoring	(4) Midterm math test score
Girl x LPA	-0.090	0.405***	-0.040	3.340
	(0.082)	(0.068)	(0.058)	(2.123)
Hours prep + grading: hours in class x LPA	-0.024	0.017	-0.002	1.053**
	(0.022)	(0.019)	(0.016)	(0.505)
Hours prep + grading: hours in class x LPA x girl	0.016	-0.034	0.016	-0.535
	(0.032)	(0.024)	(0.022)	(0.760)
Girl	0.042***	-0.152***	0.043**	0.573
	(0.012)	(0.029)	(0.019)	(0.502)
LPA	0.012*	0.017	-0.015*	-0.195
	(0.006)	(0.013)	(0.008)	(0.354)
Hours prep + grading: hours in class	0.554***	-0.194***	-0.000	-11.211***
	(0.058)	(0.046)	(0.036)	(1.343)
Hours prep + grading: hours in class x girl	0.554***	-0.194***	-0.000	-11.211***
	(0.058)	(0.046)	(0.036)	(1.343)
Number of observations	8,212	8,055	8,193	8,230

Notes: The dependent variable in question is given in the column heading. Robust standard errors clustered at the school level are shown in parentheses, and the coefficients are estimated using the specification in Equation 3. * p<0.1, ** p<0.05, *** p<0.01.

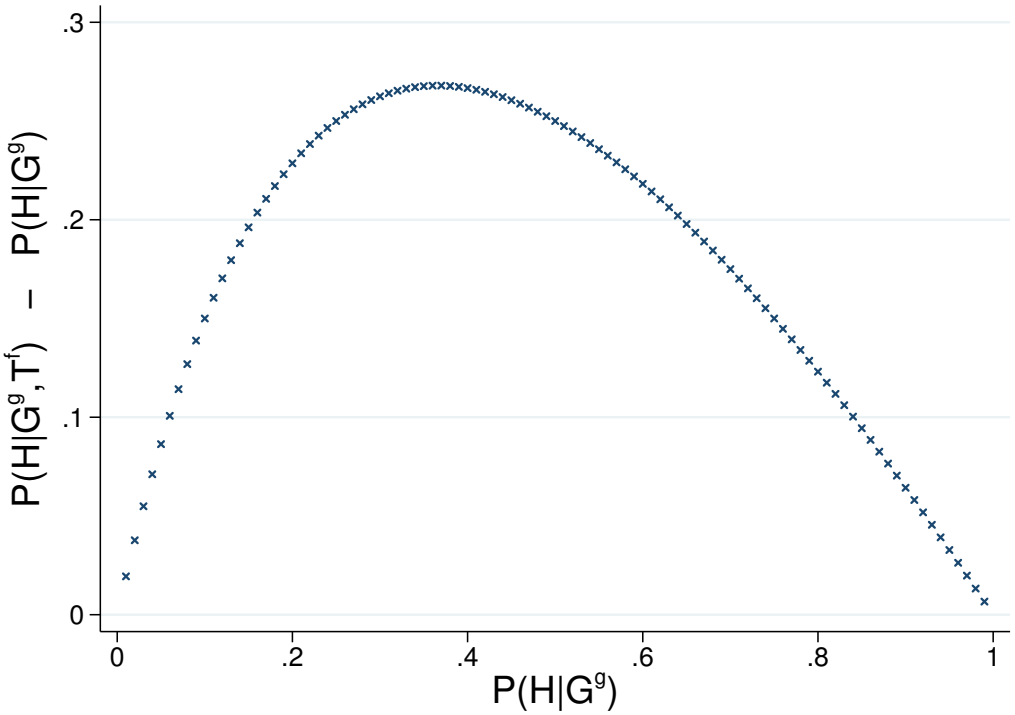
Table A.11: Teaching method

	Discuss in small groups		*Students and teacher "interactively" discuss*	
	(1) Perceived difficulty of current math class	(2) Midterm math test score	(3) Perceived difficulty of current math class	(4) Midterm math test score
Uses teaching method	0.011	-0.456	0.007***	-0.144
	(0.020)	(0.954)	(0.028)	(1.164)
Uses teaching method x girl	-0.008	0.219	-0.033***	-0.522
	(0.013)	(0.487)	(0.022)	(0.622)
Uses teaching method x LPA	0.028	0.011	-0.030	-1.149
	(0.048)	(1.232)	(0.050)	(1.313)
Uses teaching method x girl x LPA	0.011	-1.035	0.048	-1.575
	(0.063)	(1.530)	(0.066)	(1.554)
Number of observations	8,257	8,275	8,251	8,268

Notes: The dependent variable in question is given in the column heading. Robust standard errors clustered at the school level are shown in parentheses, and the coefficients are estimated using the specification in Equation 3. * p<0.1, ** p<0.05, *** p<0.01.

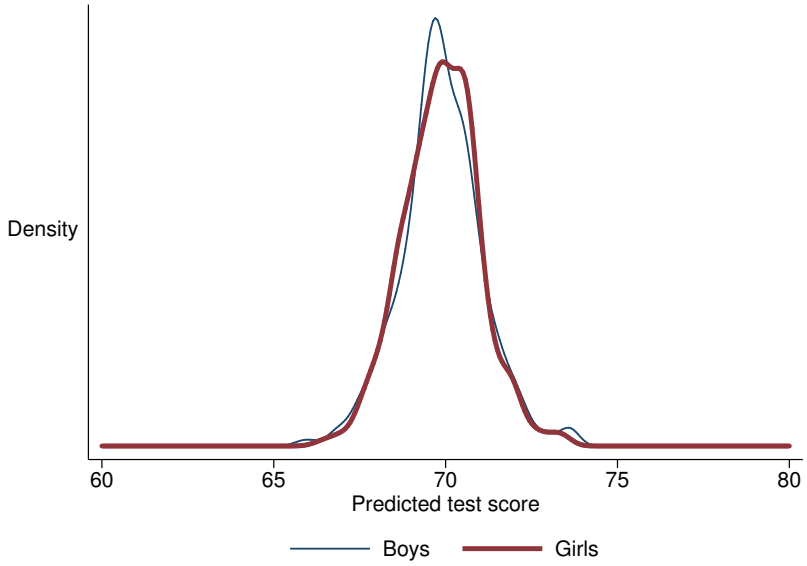
Appendix B: Appendix figures

Figure A.1: Mapping of prior to size of update

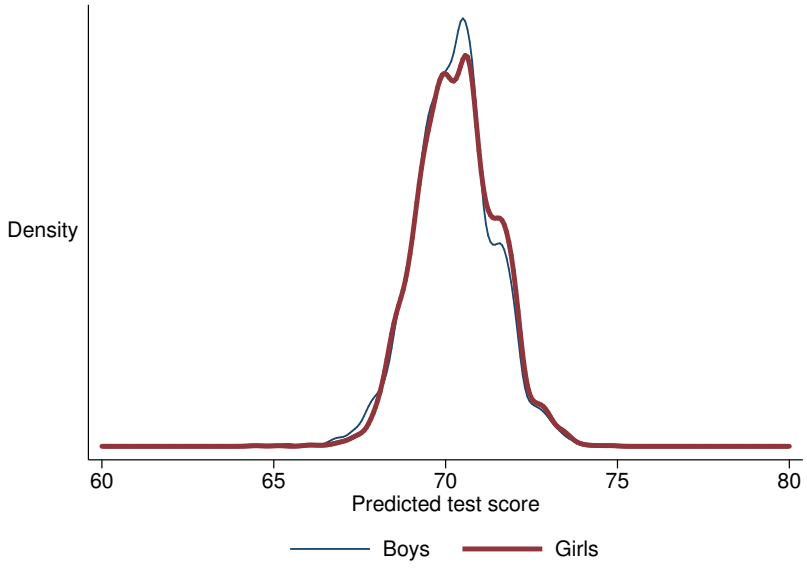


Notes: this figure shows the mapping from a girl's prior that she is of high ability, $P(H|G^g)$, to the update of that prior in response to encountering a female math teacher. The assumptions used to generate this figure are $P(G^g, T^f|H) = 0.6$ and $P(G^g, T^f|L) = 0.2$, but the right-skewness of the mapping generally holds under $P(G^g, T^f|H) > P(G^g, T^f|L)$.

Figure A.2: Predicted test score distributions, by perceived ability



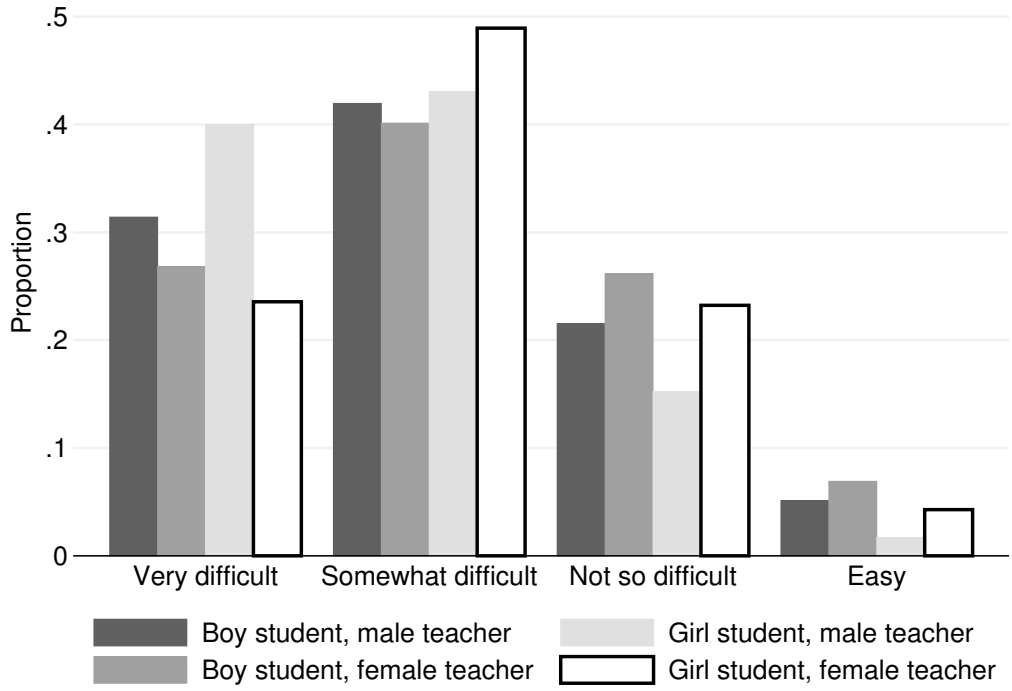
Panel A: Low perceived ability



Panel B: Not low perceived ability

Notes: to generate these figures, we regress test scores on the vector of student-level predetermined characteristics and, using these coefficients, generate a predicted test score for each student. We then plot these using a gaussian kernel for each perceived ability-gender group.

Figure A.3: Effect of teacher-student gender match on student beliefs, for those below within-group median test score



Notes: this figure shows the same analysis as reported in Figure 3, only limiting the sample instead to those below the within-group median math test score.

Appendix C: Comparing estimates from random and non-random assignment

While sorting students by ability in middle school is highly discouraged by the Chinese government, China also has a history of mixed fidelity of implementation of central directives (Serrato et al., 2016). This is borne out in our data, where approximately 25% of schools (and 15% of seventh grade classes) report allowing sorting of students according to prior performance. As in LaLonde (1986), we use these schools as an opportunity to generate estimates of another parameter of interest - the difference between an estimate of β_3 generated using data with random assignment of students to classes and an estimate of β_3 generated using data without random assignment. We will call this parameter $\tilde{\beta_3}$, defined formally as:

$$\tilde{\beta_3} = \beta_3^{random} - \beta_3^{non-random} \tag{4}$$

In addition to LaLonde (1986), this approach has been used in observational and experimental contexts to estimate the extent of the difference between estimates with random and non-random assignment in economics (Heckman et al., 1998; Glewwe et al., 2004) and in several meta-analyses from the medical literature (Schulz et al., 1995; Concato et al., 2000).

It is important to note that we do not have an experiment which randomized the student assignment mechanism. Instead, we observe whether the school reports using a random assignment mechanism. As a result, the estimate we generate of $\tilde{\beta_3}$ is likely to be biased, as there is almost certainly some external factor determining whether or not the school uses a random assignment mechanism to place children in their seventh grade classes and this may also influence the magnitude of the β_3 estimate. Indeed, in observational data, we see differences in rural/urban location of schools with different assignment mechanisms, as well as in the training levels of female teachers. Nonetheless, despite the fact that this approach will not yield an unbiased parameter estimate, ours is the first attempt we are aware of to generate such an estimate in this literature.

We present four results: estimates of the two β_3 parameters, using the random and non-random samples, respectively, $\tilde{\beta_3}$, the difference between the two, and then this difference as a proportion of the non-random β_3. We show these results in Table A.12, increasing controls and adding fixed effects as we go from column 1 to 5. A few key results arise from this analysis - the first is that es-

Table A.12: Effect estimates from random and non-random teacher assignment

	(1)	(2)	(3)	(4)	(5)
β_3^{random}	1.059	1.030	0.971	0.864	0.931
$\beta_3^{non-random}$	0.832	0.860	0.870	0.757	0.701
$\tilde{\beta}_3$	0.227	0.171	0.101	0.106	0.229
Measure of attenuation [(β_3^{random} / $\beta_3^{non-random}$)-1] * 100	27.2%	19.8%	11.6%	14.0%	32.7%

Notes: the dependent variable is again the student's math test score, and the estimates are generated using Equation 3 after removing all variables relating to low perceived ability. The specifications in columns 1-5 here proceed as follows: column 1 uses no controls, column 2 adds child-level controls, column 3 adds the full set of controls aside from the fixed effects, and column 4 and 5 include school- and school-by-grade fixed effects, respectively. In each of these regressions, there are 8,345 observations for the randomly assigned sample and 8,998 for the non-randomly assigned sample.

timates generated using the random sample are between 11 and 33% larger than those generated using the non-random sample. The largest of these gaps is in the fifth column, which we argue is the most credible comparison: estimating the difference between girls assigned to female and male math teachers, within a grade within a given school, using the full set of child and teacher controls. The second is that these gaps are qualitatively similar to the gaps between our larger estimates and the (smaller) estimates in prior work generated using data from contexts where students are assigned to classes using a non-random mechanism.