ISSN 2042-2695

CENTRE for ECONOMIC PERFORMANCE

CEP Discussion Paper No 1341

March 2015

Giving a Little Help to Girls? Evidence on Grade Discrimination and its Effect on Students' Achievement

Camille Terrier

Abstract
This paper tests if gender-discrimination in grading affects pupils' achievements and course choices. I use a unique dataset containing grades given by teachers, scores obtained anonymously by pupils at different ages, and their course choice during high school. Based on double-differences, the identification of the gender bias in grades suggests that girls benefit from a substantive positive discrimination in math but not in French. This bias is not explained by girls' better behavior and only marginally by their lower initial achievement. I then use the heterogeneity in teachers' discriminatory behavior to show that classes in which teachers present a high degree of discrimination in favor of girls are also classes in which girls tend to progress significantly more than boys, during the school year but also during the next four years. Teachers' biases also increase the relative probability that girls attend a general high school and chose science courses.

Keywords: Gender, grading, discrimination, progress
JEL codes: I21, I24, J16

This paper was produced as part of the Centre's Education Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

I would especially like to thank my advisor Marc Gurgand. This paper also benefited from discussions and helpful comments from Elizabeth Beasley, Anne Boring, Thomas Breda, Ricardo Estrada, Julien Grenet, Alexis Le Chapelain, Eric Maurin, Sandra McNally, Thomas Piketty, Steve Pischke, Corinne Prost, as well as participants at the Paris School of Economics Applied Economics Seminar, Third Lisbon Research Workshop on Economics, Statistics and Econometrics of Education, University College London RES PhD Conf, University of Southern Denmark Applied Micro Workshop, Sciences-Po Paris LIEPP Education Seminar, French Ministry of Education Workshop and European Doctoral Program in Quantitative Economics Jamboree. I am especially grateful to Francesco Avvisati, Marc Gurgand, Nina Guyon and Eric Maurin for sharing their dataset, as well as to the Direction de l'évaluation, de la prospective et de la performance (DEPP) of the French Ministry of Education for giving me access to complementary data used in this paper.

Camille Terrier , Paris School of Economics and Centre for Economic Performance, London School of Economics.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

1 Introduction

This paper is related to two puzzles in pupils' success at school. First, in most OECD countries, a persistent achievement gap exists between boys and girls at the earliest stage of schooling. Boys tend to outperform girls in mathematics, whilst the opposite is observed in languages (Fryer and Levitt 2010, OECD 2009)[1]. Second, in many countries girls catch up with boys in mathematics over the years, so that the aforementioned achievement gap vanishes. In French however, boys do not catch up and girls tend to keep their advance. This opposite pattern implies that in many countries, by the end of secondary school, girls outperform boys at school[2]. These puzzles raise two questions: how to explain the early achievement gap between boys and girls ? Why does it seem to vanish in math but persist in humanities?

This paper sheds new light on gender biases in teachers' grades and provides evidence on the impact of such biases on pupils' progress. Gender gaps in achievement are of particular concern since they might cause greater subsequent inequalities in tracks chosen, subjects of study at university, and wages (Heckman et al. 2006). In an effort to understand the origins of these gender inequalities, research has proven that teachers' stereotypes affect their pupils' success, notably because stereotypes can bias teachers' assessment and grades (Bar and Zussman 2012, Burgess and Greaves 2009, Hanna and Linden 2012). In mathematics, teachers have often been thought to have negative stereotypes towards girls. Girls would be less competitive than boys, less logical, less adventurous and would rely more on effort than on ability to succeed (Tiedemann 2000, Fennema and Peterson 1985, Fennema et al. 1990).

A number of papers have shown that girls benefit from grade discrimination (Lindhal 2007, Lavy 2008, Robinson and Lubienski 2011, Falch and Naper 2013, Cornwell et al. 2013). Most of these results are based on a comparison between blind scores and teachers grades, a methodology introduced in a seminal paper by Lavy (2008). Yet, there is no clear consensus in the existing literature. Some papers find no gender discrimination (Hinnerich et al. 2011). Ouazad and Page (2013) and Dee (2007) observe that gender discrimination depends on teachers' gender, while Breda and Ly (2012) find that discrimination depends on the degree to which the subject is "male-connoted". Besides the inconclusive nature of this literature, most previous papers are not able to disentangle a pure gender bias from a discrimination related to pupils' behavior. Hence the risk of biased estimates due to omitted variables. A contribution of this paper is to

[1] International comparative studies of educational achievement provide evidence of this early gender gap. In the 2011 TIMSS assessment of mathematical knowledge of 4th grade pupils, of the 24 countries with a statistically significant gender difference, 20 had differences favoring boys – among which the United States, Finland, Norway, Austria, Korea, Germany and Italy. Regarding reading and writing, in nearly all of the 45 countries participating to the PIRLS assessment, 4th grade girls outperformed boys in the reading achievement in 2011.

[2] In math, TIMSS assessments have shown gender differences in achievement to favor boys on average at the fourth grade, but to disappear or favor girls at the eighth grade, although the situation varies considerably from country to country. On the contrary, recent research in the United States finds that girls have an advantage in reading at all grades from kindergarten through the eighth grade (Robinson and Lubienski 2011,), and PISA 2009 reports that 15-year-old girls perform consistently better in reading than boys (Machin and Pekkarinen 2008, OECD 2009).

address this concern.

Another key question is whether grade discrimination affects pupils' progress. There is very little research measuring the effects of gender biases on pupils' subsequent progress. All prior research have focused on potential mechanisms through which discrimination could affect progress. Jussim and Eccles (1992) study how teachers' expectations influence student achievement through self-fulfilling prophecies. Positive biases could also reduce 'stereotype threats'. The latter arise when girls or minority groups perform poorly for the sole reason that they fear confirming the stereotype that their group performs poorly (Steele and Aronson 1995, Hoff and Pandey 2006). The apprehension it causes might disrupt women's math performance (Spencer et al. 1999). Therefore, over-grading girls can reduce their anxiety to be judged as poor performers when they undergo a math exam. Additionally, teacher-assigned grades have been proven to affect students' math self-concept and interest (Trautwein et al. 2006, Marsh and Craven, 1997), which can affect their achievement (Bonesronning, 2008). Finally, Mechtenberg (2009) provides a theoretical model of how biased grading at school can explain gender differences in achievements[3]. The link between biased grading and pupils' achievement has long been an important research question in education sciences, but not in economics. To my knowledge, this is the first paper to provide empirical evidence on how grade discrimination affects pupils' progress over the short and long-term, along with a contemporaneous and independent study by Lavy and Sand (2015)[4].

I use a rich student-level dataset produced by Avvisati et al. (2014). Three features make this dataset unique. Firstly it includes two different measures of a pupil's ability: a 'blind' score and a 'non-blind' score. This enables me to identify the gender bias. 4490 pupils in 6th grade were required to take a standardized test at the beginning and at the end of the year. These tests were graded anonymously by an external corrector. They can be considered as blind scores free of any teachers' stereotypes. In addition to these blind scores, grades attributed by teachers were collected during the school year – hence non-blind and potentially affected by teachers' stereotypes. As long as both blind and non-blind scores measure the same skills, the blind score can be considered as the counterfactual measure to the non-blind score. A second advantage of this dataset is that it contains extensive information on pupils' behavior in the classroom. This allows me to disentangle grade favoritism related to gender from favoritism related to pupils' behavior. Finally, the third key feature of these data is that we can follow pupils over time. Blind scores are available at three different periods: beginning and end of the 6th grade, and end of the 9th grade. Information is also available on pupils' course choice during high school. This gives me the unique opportunity to study the impact of gender discrimination on pupils' progress (over the short and long-term) and course choice.

[3]School results are defined as a combination of talent and effort, the latter being the channel through which grade discrimination could affect future cognitive achievement.

[4]Lavy and Sand (2015) analyze a similar question by using the difference between teachers in the degree of stereotypical attitude, and the conditional random assignment of pupils to classes to identify the effect of teachers' attitudes on boys and girls progress separately.

I use a double-differences (DiD) strategy to identify the existence of gender biases in grades. Discrimination is defined as the average gap between non-blind and blind scores for girls, minus this same gap for boys. Prior research has used this method to estimate gender discrimination (Falch and Naper 2013, Breda and Ly 2012, Lavy 2008, Goldin and Rouse 2000, Blank 1991). Overall I find strong evidence for a substantial bias in favor of girls in math, representing 0.31 points of the s.d. No discrimination is observed in French. Controlling for pupils' punishment does not affect significantly the estimate so that the gender discrimination does not capture a "good behavior bias". However, controlling for pupils' achievement at the beginning of the year slightly decreases the gender bias in math, due to the fact that girls perform lower than boys in this subject, and that low performers tend to be favored by teachers. These results are robust to a variety of alternative specifications that account for the fact that the blind and the non-blind scores might not measure the same abilities, that they are not filled in at the same date, and finally that girls might be more stressed than boys for national evaluations. These findings shed new light on the role of girls' behavior in teachers' gender bias. They tend to confirm existing studies which find that girls are favored by teachers in math (Falch and Naper 2013, Breda and Ly 2012).

Then, based on the preceding robust estimation of teachers' biases, I focus my analysis on the effect of these biases on girls' progress and course choice, compared to boys. The identification strategy, based on class level data, exploits the high variation in teachers' discriminatory behavior: not all teachers favor girls, and among those who have a biased assessment of girls relative to boys, some are more biased than others. Taking advantage of both this heterogeneity and the quasi-random assignment of pupils to teachers who discriminate, the identification stems from a comparison of the relative progress of girls (as compared to boys) in classes where the teacher displays a high degree of discrimination, to the progress of girls in classes where the teacher does not discriminate much.

The key finding is that classes in which girls benefit from a high degree of positive discrimination are also classes in which girls progress more (relative to boys) during the 6th grade and over the long term. Girls perform initially lower than boys in math but catch up during the 6th grade. I find that the reduction of this achievement gap between boys and girls is entirely driven by teachers discriminatory behavior. Over the longer term, half of catching up is explained by teachers' biases. Additionally, I find that gender discrimination affects girls course choice compared to boys. Girls are relatively more likely to attend a general high school (rather than a professional or technical one), and to chose scientific courses in high school. All together, these results show that positively rewarding pupils has the potential to affect their progress and course choice. This is consistent with two mechanisms mentioned in prior literature. In math, favoring girls can reduce the stereotype threat they suffer from, and hence reduce their apprehension when filling in an exam. This could explain why, over the short term, biases affect girls' relative progress in math but not in French, a subject in which girls might suffer less from stereotypes threats. Positive biases can also affect girls' interest and self-confidence in a subject. However,

my results tend to challenge Mechtenberg's (2009) theoretical predictions according to which, due to their awareness of receiving biased grading, girls would be reluctant to internalize good grades in math.

Taken together, these results build upon an important literature suggesting that teachers' grades are biased. My findings confirm the existence of such biases, but more importantly they highlight that gender discrimination can have long-lasting effects on girls' human capital accumulation relative to boys. I provide a new explanation for the fact that the achievement gap vanishes in math but persists in French. This is particularly relevant for the ongoing debate about policies aimed at promoting gender equality at school. Advocates of such policies usually focus their argumentation on the fact that teachers' grades can be a source of inequalities at school. My findings bring this argument one step further by highlighting that, over the long term, teachers' biases can also play a large and lasting role in the reduction of the gender achievement gap at school.

The article proceeds as follows. Section 2 presents the dataset and gives some descriptive statistics. Section 3 defines a simple model of grade attribution, discusses the identification of gender discrimination in grades, and presents the results. Section 4 presents a model of pupils' progress, discusses the identification of the causal effect, and presents the results. Section 5 concludes.

2 Data

2.1 The dataset

I address the question of teachers' assessment bias by using a French dataset which contains 35 secondary schools, 191 classes, and 4490 pupils in 6th grade, hence 11 years old. Three features of this dataset are particularly interesting for this study. First, this dataset provides two different sources of information on pupils' achievements. The first one is the score obtained by students to a standardized test they complete at the beginning of the school year. This test has been created by the French Education Ministry and is taken every year by all French pupils who enter the 6th grade in order to assess their cognitive skills. It is identical across schools and tests knowledge on French and mathematics. The important feature of this test is that it is externally graded so that the grader has no information on the name, gender, social background or school attended by pupils. Hence, these scores may safely be assumed to be free of any bias caused by stereotypes from an external examiner. The second source of information on children' achievement is provided by teachers' assessment of their own pupils. A pupil has a different teacher in each subject and all teachers report pupils' average grade on end-of-term report cards. In this study, I focus on mathematics and French grades given during the first and last term of the school year. In so far as teachers have permanent contacts with the pupils they teach, these average grades may reflect biases from teachers' gender stereotypes. Thus, I have two different scores that measure students' knowledge. I use the term "blind scores" to describe

test scores that have been anonymously graded. When grades have been given by teachers who know pupils' gender and identity, I describe them as "non-blind scores"[5].

The second interesting feature of this dataset is that it contains a rich set of measures of pupils' behavior for each of the three school terms. I have information on whether pupils were given an official "disciplinary warning", whether they were definitively excluded from the school, temporarily excluded from the school or from the class, whether they were put in detention or received blâmes[6]. Temporary exclusions signal violent behavior or repeated transgressions of the rules. They are decided by the school head. All these sanctions can be cumulated by pupils.

The third key aspect of this dataset is that we can follow pupils over time: blind scores and schooling decisions are available several years after the sixth grade. This enables me to estimate the effect of the gender bias on pupils' progress and course choice. Regarding progress, a pupil's achievement is measured by blind scores at the end of the 6th grade and at end of the 9th grades (on top of the blind score given at the entrance of grade 6). The test completed at the end of grade 6 is extremely similar to the one pupils take when they enter grade 6. The knowledge tested are similar and the properties of this test are the same as described above : created by the French Education Ministry, identical across schools, externally graded. Then, at the end of grade 9, which is also the end of lower secondary school, all pupils have to take a national exam to obtain the 'Diplome national du brevet'. This externally graded score constitutes the final blind measure of pupils' ability in this study[7]. Finally, additionally to these scores, information is available on pupils' schooling decisions and course choice in high school. The 9th grade corresponds to the last grade of the lower (and compulsory) secondary school. After this grade, pupils can chose between the vocational, technical or general training. For those who decide to follow a general training, pupils have to specialize when they enter the 11th grade, by choosing one of the three following options: sciences, humanities or economics and social sciences. I use this information to estimate the effect of teachers' gender biases on three outcomes : pupils' probability to undergo a general training, to follow scientific courses, and to repeat a grade. Information on pupils' long-term outcomes comes from the statistical department of the French ministry of education. It has been merged to the initial dataset. An analysis of the attrition is done in section 4.4. Overall, respectively 18.9% and 19.6% of the French and math scores are missing at the end of the 9th grade. For 20.9% of the pupils, we do not have information on their course choice during the 11th grade.

[5]It is worth mentioning that the standardized tests are high-stakes for neither the students nor the teachers. For students, they are a pure administrative evaluation aimed at reporting pupils' average achievement by schools to the Ministry. For teachers, their evaluations or salaries do not depend on their pupils' results to these tests so that they have no incentive to 'teach to the test'. The standardized tests are also taken in the same conditions as ordinary class exams: pupils fill in the test in their usual classroom and their teacher gives the instructions. Only the content of the tests differ, an issue that I will discuss further in the paper.

[6]Blâmes are official warnings given by the school's administration when a pupil behaves badly in a repeated way.

[7]It is worth mentioning that contrary the 6th grade blind scores, the 9th grade score is high-stake for the pupils.

Finally, the dataset contains information on teachers' gender, birth date and years of experience, as well as administrative information on children: gender, parents' profession, grade retention and birth date. The schools included in this dataset are mostly located in deprived areas. Therefore they are not representative of all French pupils, an issue that I will discuss in a further section.

2.2 Descriptive statistics and balance check of attrition

The dataset contains 4490 pupils. The first column of table 1 presents descriptive statistics. 48.1% of the pupils in this sample are girls and 68.6% have low SES parents, which is consistent with the fact that most schools in this study are located in the deprived administrative area of Creteil. Regarding attrition, for 526 pupils (11.7%), one or more test score is missing during first term so that the sample is unbalanced. Missing scores might be blind or non-blind scores, in math or French. The sample of pupils with no missing grades in math and French contains 3964 observations – 4068 in math only and 4058 in French. In order to test if pupils with one or more missing variables are different from those with no missing variables, I implement a balance check of the attrition and compare several characteristics across both groups of pupils. Results are presented in table 1.

Pupils for which one or more test score is missing have different characteristics from pupils with no variable missing. They have systematically lower test scores in both blind and non-blind scores. For instance, in French during first term, their blind score is on average 0.283 points lower. There are also 7.9 percentage points fewer girls in the sample with missing variables, and pupils' seem to have a slightly worst behavior. Parents belong less to high or low SES, hence we can expect parents being more middle class.

Considering these differences, analyzing discrimination with the sole balanced sample is not satisfactory. Although this sample allows comparing results obtained with the same subset of pupils, it might yield results that suffer from a selection bias, hence being non-representative of the whole sample. In the remaining of the paper, I systematically run regressions on both samples: the sample of 3964 observations with no missing variable and the one with the maximum number of observations (4490) but some variables missing. Every time results differ, I will point it out.

2.3 Descriptive statistics

Table 2 and density graphics present statistical differences between boys' and girls' scores. In the remaining of the paper, all descriptive statistics and analysis are performed on standardized test scores – mean zero and variance equal one. Standardization is done within score (blind and non-blind), subject and term.

Graphics 1 and 2 display distributions of blind and non-blind scores during the first term in French. In this subject, girls strongly outperform boys, and this premium is not affected by the nature of the grade (blind or non-blind). As reported in table 2, girls' average score is 0.434 points higher than boys when the score is blind and 0.460 when it is non-blind. However, the story is different in mathematics. Figures 3 and 4 show that boys outperform girls when grades are blind, but the opposite is observed when teachers assess their pupils. Hence, girls' average score during first term is 0.147 points lower than boys when the score is blind but it is 0.170 points higher when it is non-blind. Graphically, a clear shift to the right of girls' score distribution is observed (relative to boys) when comparing blind and non-blind scores in math.

Graphics 5 to 10 present girls' and boys' evolution of blind scores between the beginning and the end of the 6th grade, hence capturing their relative progress. In math, the initial boys' premium vanishes between the first and last term of the 6th grade. Girls progress more than boys so that, by the end of the year, the average gap between boys' and girls' scores in math is no more statistically significant. Three years later, by the end of 9th grade, girls at the bottom of the distribution are even performing better than boys. The average achievement gap represents 0.058 points and is in favor of girls. One of the objectives of this paper is to determine whether part of this catching up is the result of encouragement generated by grade bias in favor of girls. In French, no clear difference in progress between boys and girls is observed.

3 Gender discrimination in grades

3.1 Model of grade attribution

I define a simple model to describe how blind and non-blind scores are attributed. The main assumption of this model is that blind scores are free of any bias, and should only measure pupils' ability, whereas non-blind scores can be affected by teacher's stereotypes towards boys or girls. Hence, blind scores are modeled as a function of a pupil's ability only:

$$B_i = \theta_{1i} + \epsilon_{iB} \tag{1}$$

Here θ_{1i} is a pupil's ability, B_i is a noisy measure of a pupil's ability, and ϵ_{iB} corresponds to an individual random shock specific to blind scores. This might capture any effect that makes a pupil overperform or underperform the day of the exam and can be interpreted as measurement error. Non-blind scores can be affected by teachers' beliefs towards pupils' gender. Hence, they can be modeled as a function of both ability and pupils' gender:

$$NB_i = \alpha_0 + \theta_{2i} + \alpha_2 G_i + \epsilon_{iNB} \tag{2}$$

Here θ_{2i} is the pupil's ability that is measured by the non-blind test. G_i is a dummy variable that takes the value 1 for girls. α_2 is the coefficient representing the potential gender related

discrimination. The constant α_0 represents the average gap for boys between the non-blind score and the ability $(NB_i - \theta_{2i})$. ϵ_{iNB} is an individual shock specific to grades attributed by teachers. This noise might capture pupils' behavior for instance. Finally, I allow θ_{1i} and θ_{2i} to differ, meaning that abilities measured by blind and non-blind scores might differ. The relationship between both abilities can be modeled as follows:

$$\theta_{2i} = \rho\theta_{1i} + v_i \tag{3}$$

Where v_i captures variables that potentially affect ability measured by class exams θ_{2i}, once controlled for ability measured by blind score θ_{1i}. Any specific ability measured by class exams but not by standardized tests, would be captured by v_i. I discuss further in the next section the importance of differentiating abilities measured by both tests. Ability measured by blind scores (θ_{1i}) might include pupils' long-term memory and their ability to synthesize knowledge acquired in the last few months, while ability measured by non-blind scores (θ_{2i}) might integrate more short-term skills such as learning an exercise by heart and replicating it the day after for the class exam. Any difference between θ_{1i} and θ_{2i} could bias the identification of discrimination. If the blind and the non-blind scores measure slightly different abilities, and if boys or girls are more endowed in one of these abilities, then the coefficient α_2 of gender would not only measure a potential discrimination, but also the difference in ability distribution between boys and girls.

This way of modeling blind and non-blind scores is highly simplified and relies on two important hypotheses. Firstly, I suppose a linear relation between non-blind scores, ability and gender. Secondly, I assume that non-blind scores do not depend on blind scores in this specification. This hypothesis is likely to be satisfied in our context because blind tests were not corrected by teachers but by independent correctors.

The reduced form of this structural model is obtained by replacing θ_{2i} by its formula in equation (2):

$$NB_i = \alpha_0 + \rho\theta_{1i} + \alpha_2 G_i + (\epsilon_{iNB} + v_i) \tag{4}$$

Replacing θ_{1i} by $(B_i - \epsilon_{iB})$ gives the final reduced form:

$$NB_i = \alpha_0 + \rho B_i + \alpha_2 G_i + (\epsilon_{iNB} + v_i - \rho\epsilon_{iB}) \tag{5}$$

It is worth mentioning that this model could be used to study other sources of discrimination. For instance, biases in grades related to pupils' behavior, their academic level or their social background could be studied by replacing G_i by other interesting variables in equation (5).

3.2 Identification strategy for discrimination

To identify a potential gender bias in grades, I first use a double-differences strategy. This methodology has been introduced in a seminal paper by Lavy (2008) and widely used by later papers to estimate discrimination: Falch and Naper (2013), Breda and Li (2012), Goldin and Rouse (2000) and Blank (1991). The strategy consists of estimating the difference between

boys' and girls' average gap between the non-blind and the blind scores. In the absence of teachers' biases in grades, and under the assumption that both tests measure the same abilities, the difference between the non-blind score and the blind score should be the same for boys and girls. This corresponds to the common trend identification hypothesis. Implementing a double difference controls for the average effect of non-blind grading on scores, for the average effect of being a girl on score, so that what the double difference captures is the specific effect of the grade being non-blind on girls scores, relative to boys.

One of the advantages of the reduced form equation (5) is that it is compatible with an identification based on double-differences, provided that the following assumptions are made: blind and non-blind scores are assumed to measure the same abilities, so that $\theta_{2i} = \theta_{1i} = \theta_i$. In equation (5) this is equivalent to $\rho = 1$ and $v_i = 0$. This hypothesis is often implicitly made in other papers. I make it clear here, and will discuss its robustness in a further section, by analyzing the identification of discrimination in the more general setup where both tests do not measure the same abilities. To begin with, I consider this assumption as valid, so that equation (5) is equivalent to the usual double-differences equation:

$$NB_i - B_i = \alpha_0 + \alpha_2 G_i + (\epsilon_{iNB} - \epsilon_{iB}) \tag{6}$$

A more common formulation of this DiD specification is written below. The estimates obtained for discrimination are similar but equation (7) has the advantage of providing coefficients for the gender effect and the non-blind effect:

$$Sco_{in} = \alpha + \beta G_i + \gamma NB_i + \alpha_2 (G_i * NB_i) + \pi_c + \epsilon_{in} \tag{7}$$

Here Sco_{in} is the grade received by a pupil when the nature of scoring is n (n=1 for non-blind and 0 for blind). Hence, for each pupil, this dependent variable is a vector of both blind and non-blind grades received. G_i is a dummy variable equal to 1 if the pupil is a girl. NB_i is a dummy variable equal to 1 if the score has been given non-anonymously by a teacher. The coefficient I am interested in is the coefficient α_2 of the interaction term which identifies gender discrimination. Finally, π_c is a class fixed-effect aimed at capturing elements affecting grades in a given class: teachers' severity for instance, or student/teacher ratio, peers effects... In further specifications, additional control variables will be added such as pupils' behavior, parents' profession, or pupils' initial level.

3.3 Empirical results on discrimination

Table 3 presents the coefficient estimates of equation (7). Two different regressions are run in math (columns 1 and 3) and French (columns 2 and 4). In all specifications, standard errors are estimated with school level clusters to take into account common shocks at the school level. I find that in math, the coefficient of the interaction term Girl*Non-Blind is high and

significant - 0.31 points of the s.d - meaning that girls benefit from a positive discrimination in this subject. This result suggests that the extent of the bias is important: girls' non-blind scores are on average 6.2% higher than boys in math during first term due to discrimination. Using the balanced sample or the full sample does not change the results much. In addition, in French the coefficient of the interaction term is neither high nor significant, meaning that no gender bias is observed in this subject.

These results confirm up to a point what Lavy (2008) observes in his analysis: in opposition to what common beliefs about girls' discrimination would predict, the biases observed are in favor of girls. Similarly, Robinson and Lubienski (2011) find that teachers in elementary and middle schools consistently rate females higher than males in both math and reading, even when cognitive assessments suggest that males have an advantage. Contrary to both previous studies, I find a bias only in math and not in all subjects. The results of Breda and Ly (2012) are also consistent with my estimates. They find that discrimination goes in favor of females in more "male-connoted" subjects (e.g Math). Results decomposed by teachers' characteristics are provided in Appendix A.

I try now to understand why the gender bias is in favor of girls. Any characteristics of pupils that would influence teachers' grades and would not be equally distributed between boys and girls, could potentially explain teachers' bias in favor of girls. Typically, pupils' behavior in the class, pupils' initial achievement or having repeated a grade are three characteristics that could (consciously or not) influence teachers' attributed grades and are different for boys and girls. I successively test if each of these three characteristics explains the bias in favor of girls.

Controlling for pupils' behavior. If a bad behavior influences teachers' assessment (consciously or not), since boys behave worse than girls, this could affect the gender bias.[8] As far as I know, previous studies were not able to disentangle the 'pure' gender discrimination from a discrimination related to girls' better behavior than boys.[9] This is one of the contributions of this paper.

I create a variable "Punishment" that is a proxy for a pupil's bad behavior. It takes the value 1 if a pupil has received a disciplinary warning from the class council during first term or if he/she was temporarily excluded from the school. During the first term 8% of pupils received at least one sanction: 6.2% received a disciplinary warning and 3.6% were temporarily excluded from the school. Boys are punished more than girls: among pupils having at least one sanction during the first term, 85% are boys. Several schools did not provide information on their pupils' behavior, so that the punishment variable is missing for many pupils. Therefore, following regressions will

[8] In equation (6), without any controls for pupils' punishment, the latter would enter the error term, and would be correlated with the gender variable.

[9] Cornwell et al. (2013), using data from the 1998-99 ECLS-K cohort of primary school pupils, take into account pupils' non cognitive skills to explain why "boys who perform equally as well as girls on reading, math and science tests are graded less favorably by their teachers." More specifically, the authors use teachers' reported information on how well a pupil is "engaged in the classroom" and find that controlling for this variable significantly reduces or completely removes the bias in teachers' grades, depending on pupils' ethnicity and the grade considered.

focus on the sample of 2269 pupils for which punishments are non-missing[10]. This sample being different from the previous one, I run a balance check to verify if pupils' characteristics differ. No significant differences are found regarding the blind score, non-blind score, gender and parents' profession.[11]

Results are presented in table 4, column 2. Regressions are run in math only, where gender discrimination is observed. To ensure that coefficient comparisons are based on the same sample, column 1 presents results of the standard DiD regression implemented on the new sample. The coefficient for discrimination decreases when I control for pupils' behavior, but the drop is very small: the point estimate goes from 0.327 to 0.317. This suggests that in math, the gender discrimination I observe cannot be explained by girls' better behavior than boys.[12]

Controlling for pupils' initial achievement. The second hypothesis I test is whether discrimination in favor of girls partially captures two potentially related effects: (1) some teachers' might give more favorable grades to low-achievers and (2) in some classes the variance of teachers' grades might be smaller than the variance of the standardized scores. Firstly, some teachers might behave differently towards low-performers, and potentially give them higher grades than expected by their ability. If this is the case, since girls perform lower than boys in math, what I interpret as gender discrimination could partially capture a 'low-achiever' positive discrimination. Secondly, some teachers might have a lower dispersion of their grades than the dispersion of the standardized scores. For a given dispersion of blind scores in a classroom, reducing the dispersion of non-blind scores will improve the non-blind score of the weakest in the class, relatively to the scores of the best pupils. Again, since girls have initially lower scores than boys in math, a teacher who prefers a reduced dispersion of his grades will advantage girls compared to boys.

To test these hypotheses, I first add controls for pupils' initial position in the blind grade distribution. The new specification includes dummy variables indicating whether pupils belong to the lowest or highest decile of the blind score distribution. Scores are decomposed into deciles within each subject and within class, meaning that pupils are ranked relatively to other children in their class. Column 4 in table 4 presents results when a variable controlling for low achievers is included (pupils below the 1st decile) and column 5 presents results with variables controlling for both low and high achievers (pupils above the 9th decile). The point estimate of the gender bias decreases by 7.5% when controls for low achievers are added to the regression – from 0.318

[10] The sample is the full sample, minus the pupils with a missing punishment

[11] Even if schools which do not provide information on sanctions are the one with the worst behaved students, my results will be a lower bound of the effect of pupils' behavior on the gender bias.

[12] A variable that controls for pupils' bad behavior is included but girls' behavior might also affect non-blind scores through more diffuse aspects (Cornwell et al. 2013): how they behave in the classroom, how often they answer questions, the diligence they show in their work. I consider that these elements will not bias the results as long as they are a component of my definition of girls. In this case, the coefficient for gender discrimination captures some characteristics that are intrinsically linked to girls.

to 0.294 - suggesting that part of the gender bias in math captures an encouragement towards low-achiever. The gender bias coefficient further decreases (by 9.1% in total) when a dummy variable for high achievers is added.[13]

Controlling for pupils' grade repetition. The third characteristic which might influence teachers' grades and is not equally distributed for boys and girls is grade repetition. Among pupils who have repeated a grade, 62.2% are boys. As previously, I include a dummy for grade repetition in the regression. Results are presented in column 6 of table 4, and suggest that grade repetition does not explain the positive bias in favor of girls[14].

3.4 Robustness checks

3.4.1 Are both tests measuring the same abilities?

The DiD specification discussed above rests on the restrictive assumption that both tests measure the same abilities. However, if blind and non-blind scores do not measure exactly the same abilities, and if these skills are not equally distributed between boys and girls, then failing to take it into account will yield biased DiD estimates of gender discrimination. In equation (6), the coefficient α_2 which I interpret as discrimination would partly capture girls or boys specific ability in blind or non-blind scores. In this paper, I am careful about this concern since blind tests are standardized tests created by the French Education Ministry, while non-blind grades correspond to the average mark given every term by the teacher. They might measure slightly different abilities.

A way to test if both scores measure the same abilities is to directly estimate the reduced form equation (5) in which no restrictive assumption is imposed on abilities, and to verify if the coefficient ρ is significantly different from one. If not, both tests can be assumed to measure abilities which are perfectly correlated and DiD estimates can safely be assumed to be unbiased. Due to measurement error, instrumental variables are used for this estimation. The method is fully detailed in Appendix B.

As reported in table 13 of Appendix B, the IV estimate of the coefficient of interest α_2 equals 0.339 in math and 0.080 in French, which is very similar to the coefficient obtained by implementing DiD on the balanced sample – 0.323 and 0.043 respectively. This confirms my results suggesting a bias in teachers' grades in favor of girls. Additionally, the purpose of this estimation is to check whether both tests measure abilities which are perfectly correlated,

[13] As a second test, I run the regression on pupils' rank instead of pupils' test scores. Teachers' narrower or larger dispersion of their grades does not affect their pupils' ranking within the class. Hence running DiD regressions with pupils' rank as a dependent variable is a mean to control for teachers' smaller/larger variance of grades. Table 5 displays the coefficients of these regressions, which I run on the initial whole sample containing 8329 observations in math and 8315 in French. Coefficients are consistent with previous conclusions: the interaction term equals -2.2 in math, meaning that girls' average rank decreases by 2.2 when they are assessed by their teacher – going from 22 to 19.8 for instance.

[14] Finally, I test whether parents' profession has an impact on discrimination and find no significant effect of pupils' social background.

in other words if the IV coefficient of the blind score is equal to one. This coefficient ranges from 0.964 in French to 1.090 in math and in both cases I cannot reject the hypothesis that $\rho = 1$. This result suggests that the blind and non-blind tests measure skills that are perfectly correlated, and hence that implementing double-differences gives unbiased estimates of a gender bias. Hence, for further analysis, the DiD specification will be used.

Finally, in the reduced form presented above: $NB_i = \alpha_0 + \rho B_i + \alpha_2 G_i + (\epsilon_{iNB} + v_i - \rho\epsilon_{iB})$, I show in Appendix C that we can estimate how the OLS downward bias on ρ affects the estimation of our coefficient of interest α_2. Using the omitted variable bias formula, we can easily show that the OLS downward bias on ρ creates a downward bias on α_2 in math, but an upward bias on α_2 in French. This implies that the OLS estimate of α_2 is a lower bound in math. It remains high and significant (equal to 0.264 in math and 0.172 in French) as reported in table 13. This confirms that in math a substantial bias exists in favor of girls. In French, the coefficient should be interpreted more carefully. The OLS estimate is an upper bound of the gender bias. It suggests a positive effect, but any other method aimed at reducing the bias (IV or DiD) do not find any significant gender bias.

3.4.2 Could girls progress more than boys between the date of the blind test and the date of the non-blind?

Pupils take the standardized blind test during one of the first days of the school year whereas teachers' assessment is an average of several grades given by teachers during the first term. Since the first term lasts three months, this average of several grades measures a pupils' average ability about one and a half month after the beginning of the school year. This time lag between the date of the blind and non-blind scores might be problematic if girls tend to progress more than boys during this period. In particular, if teachers' biases in math appear early in the school year, it might affect girls' progress from the first weeks of the school year. In this case, the coefficient which I interpret as a gender bias in math would be an upper bound for the true gender bias.

To address this concern, I use the data that have been collected at the end of the academic year. Fortunately, the same scores have been collected - standardized tests and teachers' given grades – but the time lag is reversed during the last term. Pupils take the standardized blind test during one of the last days of the school year, while teachers' assessment is an average of several grades given by teachers during the three last months. Hence, the blind test is taken after the non-blind test. Under the same assumption that girls tend to progress more than boys during this period, my estimates of gender discrimination during the third term would be a lower bound. Computing the lower and upper bound of the estimates enables us to find a plausible interval for the gender bias.

I run the same DiD regression as before but with the third term scores. Then I compare the estimates obtained during first term (upper-bound) and last term (lower bound). The results

are displayed in table 6. The same full sample is used for both regressions. Consistent with the hypothesis that girls progress more than boys in math, the third term coefficient (0.259) is lower than the first term coefficient (0.318). The true value of gender discrimination is likely to be between 0.259 and 0.318.

3.4.3 Could girls be more affected by some unobserved shocks ?

The simple model defined in section 3 contains three unobserved shocks: (1) ϵ_{iB} corresponds to an individual shock specific to blind scores, (2) ϵ_{iNB} corresponds to an individual shock specific to non-blind scores and (3) v_i captures any specific ability measured by class exams but not by standardized tests. The DiD estimates rest on the assumption that these shocks are equally distributed for boys and girls[15]. However, if girls are systematically more stressed than boys for standardized tests[16], if they tend to be less effective than boys in environments that they perceive as more competitive (Gneezy et al 2003), if they tend to attach more importance to national evaluations, or if they are more endowed in specific abilities measured by class exams[17], the restrictive assumption would be violated and the DiD estimates could be biased.

To take these shocks into account, I run triple-differences (Breda et al, 2013) which rest on the following intuition: if girls systematically under-perform (or over-perform) for standardized tests because of an unobserved shock and if this shock is equally distributed between subjects, then girls should also have a lower blind than non-blind score in French. I do not observe this. In French, the gap between the blind and non-blind score for girls is the same as the one for boys. Comparing the coefficient for discrimination in math and French, as I do here, is equivalent to implementing within-gender between-subjects regressions – or triple differences. This is a mean to control for any unobserved shock or characteristics that differ across gender but are assumed to be constant between subjects. Typically, triple differences allow v_i to be distributed differently for boys and girls, but within gender v_i must be constant between French and math[18]. The coefficient for relative discrimination obtained with this method corresponds to the coefficient in math minus the one in French, hence 0.291 for the whole sample. I still

[15] In mathematical terms, this means that $E(\epsilon_{iNB}|G_i = 1) = E(\epsilon_{iNB}|G_i = 0), E(\epsilon_{iB}|G_i = 1) = E(\epsilon_{iB}|G_i = 0)$ and $E(v_i|G_i = 1) = E(v_i|G_i = 0)$.

[16] If girls are more stressed than boys for standardized tests, they would tend to under-perform in this kind of examination. My coefficient of discrimination would be an upper bound for true gender discrimination. However, a higher stress is unlikely because both tests are taken in the same conditions. Pupils take the standardized test and their class exam in the same classroom where they sit usually, and it is their teacher who gives the instructions. What is more, standardized tests are not high-stakes for the students. A pupil's test result is not accounted for to compute his/her end of term average score.

[17] These abilities could recover short-term memory or learning an exercise by heart and replicating it the day after for the class exam. McNally and Machin (2003) also suggest that the mode of assessment could affect the gender achievement gap.

[18] In mathematical terms, this means that $E(v_{i,french}|G_i = 1) = E(v_{i,math}|G_i = 1)$ and $E(v_{i,french}|G_i = 0) = E(v_{i,math}|G_i = 0)$. This within-pupil between-subjects method controls for any characteristic specific to girls that potentially affect teachers' biases: the fact that girls behave better, might be more attentive, more serious, more diligent.

conclude that a positive bias exists in math in favor of girls.

4 Impact of discrimination on pupils' progress

The results on gender discrimination pave the way for a new set of questions related to the impact of discrimination on pupils' subsequent achievement and subject choices at school. Positively discriminating students might encourage them to make more of an effort, and hence to increase their scores. Reversely, if achievement and efforts are substitutes, some students benefiting from positive discrimination could provide less effort, as they consider that they are good enough (Benabou and Tirole, 2002). The dataset I use has the benefit of containing blind scores at three different periods in time - at the beginning and at the end of the 6th grade, and at the end of 9th grade - as well as information on pupils' subject choices during 11th grade.

4.1 Comparisons of girls and boys progress

Figures 11 and 12 plot the distribution of boys and girls progress between the first and the last term of grade 6, while graphics 13 and 14 plot the progress between 6th grade and 9th grade - over the entire lower secondary school. I define progress as the difference between the blind score at the final period and the blind score at the beginning of 6th grade[19].

Graphically, there is clear evidence that girls progress more than boys in mathematics, whereas progress in French is similar. As reported in table 7, in math during the first term of 6th grade, girls' average score was 0.075 points below the mean. It is only 0.021 points below the mean during the last term, and becomes 0.029 points above the mean by the end of the 9th grade - hence a total increase of 0.104 points of the s.d. Since girls' blind scores were lower than boys' at the beginning of 6th grade, the fastest progress experienced by girls reduces the gap between boys and girls blind scores. This catching up of girls in math raises the question of the link between the positive bias in grades I observe in their favor in this subject and their subsequent higher progress.

4.2 Model of pupil's progress

I define a simple model aimed at isolating the effect of teachers' biased assessment on pupils' progress. To begin with, I will keep the model as general as possible so that discrimination could be considered towards any group of pupils. The main issue when evaluating the impact of grade discrimination on a pupil's progress is to disentangle the pure effect of grade biases from several other determinants that might explain a pupil's high or low progress: how much of the progress

[19] The difference between the blind score at the end of the 6th grade and the one at the beginning of 6th grade can be interpreted as a pupil's progress because both standardized tests measure the same abilities. They are designed by the French Ministry of Education and aimed at measuring the same abilities at two different periods in time.

is due to discrimination? How much is due to specific characteristics of the discriminated group? For instance, girls might have an intrinsic tendency to progress more than boys over the school year, without any discrimination. Similarly, low-achievers might have an initial higher propensity to progress than high-achievers, again independently from any discrimination. Finally, I want to take into account the fact that some teachers are more able than others to make their entire class progress. Especially, biased teachers might share characteristics that make their pupils progress more. The following model aims at isolating these various determinants of pupils' blind scores evolution over the school year. Equation (8) below describes blind scores during first term (as defined in section 2.1), while equation (9) describes blind scores during the third term (or any later period[20]):

$$B_{1i} = \theta_{1i} + \epsilon_{B1i} \tag{8}$$

$$B_{3i} = \theta_{3i} + \epsilon_{B3i} \tag{9}$$

For the remaining of the model, all variables and parameters for third term are indexed by 3. A pupil's ability has changed between the first and the last term. I model third term ability as a function of the three effects I want to disentangle: the effect of discrimination, a pupil's independent tendency to progress compared to the others and a teachers' effect on progress:

$$\theta_{3i} = \delta\theta_{1i} + \alpha G_i + \mu_i T_i + \beta D_{1i} + \omega_i \tag{10}$$

Third term ability θ_{3i} depends on three potential effects: (1) a discrimination effect caused by teachers' biased assessment of their pupils: βD_{1i}, where D_{1i} corresponds to grade discrimination during first term. Its impact on pupils' third term ability is measured by the coefficient β. It is important to understand that this coefficient captures several channels through which grade biases can affect a pupil's third term score. Motivation or discouragement are direct channels, but effort is also an important channel, as well as change in self-confidence and reduction of stereotypes threats. I will not be able to distinguish between these different channels, that are all captured by the coefficient β. (2) Second, third term ability θ_{3i} also depends on the independent tendency to progress of the discriminated group, relatively to other pupils. This is captured by the coefficient α. In this general model, G_i is a dummy variable that equals one for pupils belonging to the discriminated group. In a model where only gender discrimination is considered, G_i would correspond to a girl dummy. (3) Finally, a pupil's progress is affected by his/her teacher's ability to make the entire class progress, where T_i is a teacher dummy.

Compared to the model of discrimination presented in section 3, I assume here that the blind and non-blind tests measure the same abilities during the first term. This assumption is based on results obtained in the first part. Following the first robustness check, I could not reject the hypothesis that both scores are measuring skills that are perfectly correlated.

[20] For the sake of simplicity, I model the progress between the first and last term of grade 6, but the same model remains valid for progress between the beginning of the 6th grade and any later period.

In equation (10), I replace the coefficient for discrimination D_{1i} by $NB_{1i} - \theta_{1i}$, which corresponds to the difference between a pupil's ability and the non-blind grade attributed by his/her teacher during the first term. This corresponds to discrimination during the first term. Equation (10) becomes:

$$\theta_{3i} = \delta\theta_{1i} + \alpha G_i + \mu_i T_i + \beta(NB_{1i} - \theta_{1i}) + \omega_i \tag{11}$$

By replacing θ_{3i} by its expression in equation (11) I obtain:

$$B_{3i} = \delta\theta_{1i} + \alpha G_i + \mu_i T_i + \beta(NB_{1i} - \theta_{1i}) + \omega_i + \epsilon_{B3i} \tag{12}$$

Finally, replacing θ_{1i} by its equation gives the following reduced form of the model:

$$B_{3i} = (\delta - \beta)B_{1i} + \beta NB_{1i} + \alpha G_i + \mu_i T_i + [\omega_i + \epsilon_{B3i} + (\beta - \delta)\epsilon_{B1i}] \tag{13}$$

This reduced form equation isolates the effect of discrimination β, the discriminated group's independent tendency to progress α, and μ_i the teacher's effect. By rewriting it as below, the interpretation of the coefficients becomes straightforward: once controlled for a pupil's ability B_{1i}, for a group tendency to progress G_i, and for a teacher's average effect T_i, the coefficient β of the difference between non-blind and blind scores captures the effect induced by the fact that a pupil receives a grade higher than expected by his/her ability:

$$B_{3i} = \delta B_{1i} + \beta(NB_{1i} - B_{1i}) + \alpha G_i + \mu_i T_i + (\omega_i + \epsilon_{B3i} + (\beta - \delta)\epsilon_{B1i}) \tag{14}$$

4.3 Identification of girls' relative progress due to grade biases

The model defined above is compatible with any kind of grade discrimination (related to gender, ethnicity, achievement, behavior...). To build upon the results found in part 1, I will focus now on the identification of girls progress (relative to boys) due to gender discrimination only. Therefore, in equation (14), the group dummy G_i becomes a dummy for girls. The term discrimination will always refer to gender biases in the rest of this section. The identification strategy is based on the observation that not all teachers discriminate, and that among teachers who have a biased assessment of girls compared to boys, the degree of the bias also differs across teachers, with some teachers discriminating more than others. I take advantage of this heterogeneity in the degree of discrimination to implement a between-class analysis. It is the variance in teachers' discriminatory behavior that will identify the causal effect of teachers' biased assessment on pupils' achievement[21]. Graphically, this variance is represented by the horizontal axis of the graphics 15 and 16. We want to test if classes in which girls benefit from a high degree of discrimination (relatively to boys) are also classes in which girls progress more (relatively to boys). This identification strategy can be seen as a DiD strategy, where the treatment corresponds to

[21] Lavy and Sand (2015) use a similar method to identify the effect of teachers' stereotypical attitudes on boys and girls progress separately.

discrimination towards girls in some classes and the outcome is girls average third term blind score compared to boys.

It is worth mentioning that the impact of gender discrimination I estimate with this specification captures different elements. Teachers that tend to favor girls in their grades are also likely to have a behavior towards girls that differs from teachers who do not have biased grading. Typically, they might be more encouraging, friendlier, focus more attention on girls, or be less critical. The effect of gender discrimination on progress will capture all these effects. Even without being able to separately identify these elements, it is interesting to know if teachers' biased behaviors – with all elements it embeds – have an impact on girls' progress relative to boys.

Graphics 15 and 16 provide a good insight into this question. For each class in the sample, these graphs display the discrimination coefficient and girls' progress relative to boys during the 6th grade. The discrimination coefficient is defined as the class average difference between the non-blind and the blind scores for girls, minus this same difference for boys. It corresponds to the estimate of gender discrimination obtained with the DiD in part 1. Girls' progress relative to boys is measured as the difference between their blind score at the end of the year and this blind score at the beginning of the year, minus this same difference for boys. Graphically, there is clear evidence of a positive correlation between the degree of discrimination and the degree of progress, and this is true in both French and math. It is also interesting to see that in part 1, the results suggest that on average there is no discrimination in French. Graphic 16 clearly shows that despite this null average, there is an important variance in teachers' biased assessments, which might yield girls' higher or lower progress in these classes.

The identification strategy is based on the comparison of mean scores between classes. Based on equation 14, this requires aggregating scores at the class level for both girls and boys[22] and

[22] All variables are averaged conditionally to being a girl and having teacher T_i. Within a class, girls' average third term blind score is given by:

$$E(B_{3i}/T_i, G_i = 1) = \delta E(B_{1i}/T_i, G_i = 1) + \beta E(NB_{1i} - B_{1i}/T_i, G_i = 1) + \alpha E(G_i/T_i, G_i = 1)$$
$$+\mu_i E(T_i/T_i, G_i = 1) + E(\omega_i/T_i, G_i = 1) + E(\epsilon_{B3i}/T_i, G_i = 1) + (\beta - \delta)E(\epsilon_{B1i}/T_i, G_i = 1)$$

Symmetrically, boys' average score within a class is given by:

$$E(B_{3i}/T_i, G_i = 0) = \delta E(B_{1i}/T_i, G_i = 0) + \beta E(NB_{1i} - B_{1i}/T_i, G_i = 0) + \alpha E(G_i/T_i, G_i = 0)$$
$$+\mu_i E(T_i/T_i, G_i = 0) + E(\omega_i/T_i, G_i = 0) + E(\epsilon_{B3i}/T_i, G_i = 0) + (\beta - \delta)E(\epsilon_{B1i}/T_i, G_i = 0)$$

calculating the difference in progress between boys and girls in class c[23]:

$$(B_{3G} - B_{3B})_c = \alpha + \delta(B_{1G} - B_{1B})_c + \beta[(NB_{1G} - B_{1G}) - (NB_{1B} - B_{1B})]_c + (\omega_G - \omega_B)_c \quad (15)$$

Equation 15 corresponds to the equation aggregated at the class level which I want to estimate to identify the effect of gender discrimination on progress. It is specified as a differentiation between boys and girls average scores at the class level, so that teachers' effects disappear; they affect similarly boys and girls within a class. The double difference at the right hand side of the equation corresponds to the coefficients for gender discrimination estimated in section 3 of the paper – although here there is one coefficient per class[24]. The coefficient β identifies the effect of being assigned a teacher who discriminates girls more or less – relatively to boys – on girls' average third term blind score – relative to boys – once I control for the initial average difference between boys and girls' blind scores. This coefficient can be seen as a causal effect under the assumption that girls' assignment to a teacher who discriminates is quasi-random. In other words, being assigned a teacher who discriminates is independent from girls' unobserved characteristics ω_i that make them potentially progress more than boys, once their initial level is controlled for. I use the term quasi-random to describe the fact that pupils' assignment to teachers is not done through a proper lottery. Yet, an arbitrary assignment of girls with high predicted progress to teachers who discriminate is highly plausible for several reasons. Firstly, pupils considered in this study are in 6th grade, which corresponds to the first year of lower secondary school. When deciding the composition of classes, school heads and teachers have very little information on these new pupils, in particular it is very unlikely that they can predict their progress, and therefore influence their assigned class and teacher. Secondly, assigning teachers who discriminate to girls who have a high probability to progress more than boys would necessitate that school heads know who the teachers are who discriminate girls, which is again unlikely.

Although it is not possible to test this independence assumption, I test if the assignment to a teacher who discriminates is independent from boys and girls observed characteristics. To do so, I first regress the discrimination coefficient (defined at the class level in both French and math) on pupils' gender and find no significant effect: girls are not more assigned to teachers with a high bias than boys. This is true in French and math. Then, for both boys and girls separately,

[23] Where to simplify notations:

$$B_{3G} = E(B_{3i}/T_i, G_i = 1), B_{3B} = E(B_{3i}/T_i, G_i = 0)...$$
$$\omega_G = E(\omega_i/T_i, G_i = 1) + E(\epsilon_{B3i}/T_i, G_i = 1) + (\beta - \delta)E(\epsilon_{B1i}/T_i, G_i = 1)$$
$$\omega_B = E(\omega_i/T_i, G_i = 0) + E(\epsilon_{B3i}/T_i, G_i = 0) + (\beta - \delta)E(\epsilon_{B1i}/T_i, G_i = 0)$$

[24] It is also worth noticing that in equation 15, assuming $\delta = 1$ transforms it into a standard DiD equation:

$$(B_{3G} - B_{3B})_c - (B_{1G} - B_{1B})_c = \alpha + \beta[(NB_{1G} - B_{1G}) - (NB_{1B} - B_{1B})]_c + (\omega_G - \omega_B)_c$$

where the coefficient β obtained corresponds to the slopes of regressions lines displayed in graphics 16 and 17. For the remainder of the analysis, I use equation 15 which requires less restrictive assumptions.

I successively regress the discrimination coefficient (in math and in French) on the following set of variables : having upper class parents, having lower class parents, having repeated a grade. I find that these observed characteristics are independent from being assigned a teacher with a high level of bias. The only exception is that boys with upper class parents are slightly less likely to be assigned a teacher who discriminates in math, and that girls having repeated a grade are less likely to be assigned a teacher who discriminates in French. Finally, I argue that being assigned a teacher who discriminates is independent from girls' and boys' averaged random shocks affecting blind scores during first and last term. As long as these shocks recover pure testing noise – being ill the day of the exam for instance - it is plausible that they are independent from teachers' assignment [25].

This between-class comparison has three advantages compared to an estimation of parameters with individual observations based on equation 13. First, comparing classes rules out the issue of girls' potential higher stress than boys for blind tests. Here the double-differences nature of equation 15 implies that any effect that is common to all classes disappears. As long as pupils' assignment to teachers who discriminate is independent from their unobserved characteristics that make them progress more, then girls with higher stress for standardized tests should be equally distributed between classes. A second concern when analyzing discrimination and progress with individual observation is the potential for reversed causality caused by the fact that teachers might discriminate more pupils they believe have an ex-ante high potential for progress. In my setting, the arbitrary assignment of pupils implies that those with an ex-ante high potential for progress should be equally distributed between classes. Hence, comparing classes rules out this problem. Finally, averaging scores at the class level reduces significantly the measurement error affecting blind score when measured at the individual level.

4.4 Balance check of the attrition

Three different outcomes are used to estimate the causal effect of teachers' gender biases on girls' relative progress : the blind score at the end of 6th grade, the blind score at the end of 9th grade and pupils' subject choices during 11th grade. Not all the pupils could be followed over the long term, so two types of attrition exist : (1) an attrition at the class level when scores are missing for all pupils in a class and (2) an attrition at the individual level when within a class scores are missing for some pupils. Attrition is not problematic as such. Yet, if attrition at the class level is more important for classes with high (or low) discrimination degree, this could bias my estimate. To test this, I regress the dummy variable for missing classes on the

[25] The identification I use is based on the heterogeneity in teachers' discriminatory behaviors between different classes. It is equivalent to implement an IV strategy based on equation 13, where the term $(NB_{1i} - B_{1i})$ would be instrumented by all the interactions between teachers and girls at the class level. These interactions measure teachers' biased grading in favor of girls. The assumption detailed above - pupils' assignment to a teacher who discriminates is random - is analogous to an exclusion restriction on these instrumental variables.

discrimination coefficient[26]. Results are presented in table 8. Classes included in the analyses of the short-term and long-term progress do not differ regarding the discrimination degree of their teachers. Second, I test if the percentage of girls or boys missing in a class is correlated to the degree of bias of their teacher. To do so, I regress the percentage of girls (per class) on the gender bias. This is done successively for boys and girls. As previously, for each gender, six different regressions are run corresponding to the six columns of the table. Results are presented in table 9. Out of twelve coefficients, eleven are statistically non significant, suggesting that attrition of boys and girls is independent from teachers' gender biases.

4.5 Empirical results on girls' progress relative to boys

4.5.1 Short term progress during the 6th grade

The first regression is based on equation 15. The key result (reported in table 10) suggests that in math, classes in which teachers present a high degree of discrimination in favor of girls, are also classes in which girls tend to progress more over one school year compared to boys. The coefficient is high (0.281) and significant in math. In a class where boys and girls would have on average the same initial blind score, positively rewarding girls by increasing their non-blind score by one s.d compared to boys, would increase the gap between boys and girls third term blind score by 0.28 s.d. This effect is substantive, but we should keep in mind that the treatment is also important : increasing teachers' bias by one s.d represents approximatively an increase from the minimum to the maximum value of the bias. It might be more relevant to interpret this coefficient in light of the first part results. An average discrimination coefficient of 0.31 was found in math, which implies that, proportionally, girls' third term blind score would increase by 0.089 points - or 1.7% - compared to boys[27]. This effect of teachers' biases on progress during the 6th grade is observed in math but no significant effect is observed in French over the short term, partly because the standard-error of the estimate is high.

[26] Six different regressions are run for each missing variable : blind score in French and math at the end of the sixth grade, blind score in French and math at the end of the ninth grade, and information on course choice during the eleventh grade (regressed on discrimination in both French and math).

[27] We should be careful when interpreting the coefficient and keep in mind that the outcome is relative. It corresponds to the difference between girls and boys scores, so that the positive coefficient I find could correspond to a higher progress for girls than for boys, or a blind score that remains constant for girls between first and last term but decreases for boys (due to their feeling of being negatively discriminated compared to girls for instance). Lavy and Sand (2015) provide evidence that teachers' biases in favor of boys have an asymmetric effect on boys and girls. Boys achievement increases while girls' achievement is negatively affected.

4.5.2 Long-term progress until the 9th grade

Beyond the short-term effect, it is interesting to see if the effect of teachers' gender biases during the 6th grade persists over the long term, and if the girls favored by their teachers continue to catch up boys in math. To answer this question, I analyze pupils' progress until grade 9, hence four years after the gender bias is observed. The same specification is used and results are reported in columns 3 and 4 of table 10. Teachers' gender biases during grade 6 have a high and significant long-term effect on girls' progress relative to boys, in both math and French. Once controlled for the achievement gap between girls and boys at the beginning of the lower secondary school, increasing girls' grades by 1 s.d compared to boys will increase the gender achievement gap at the end of lower secondary school by 0.375 points in math and 0.421 in French. As previously, the magnitude of this effect can be interpreted with regard to the average gender bias found in the first part of the analysis. For the average estimate of teachers' bias, girls' long term achievement would increase by 0.116 s.d in math and 0.131 in French, compared to boys. This long-term effect observed in French is interesting. It shows that despite the fact that we found no average bias in teachers' grades, there exists an important variance in teachers' discriminatory behaviors which has an effect on girls' relative progress.

To build upon these results, it is interesting to see whether the catching up of girls that we observe in math, first during the 6th grade, and then until the 9th grade, would still have occurred without the gender discrimination. The descriptive statistics presented in table 2 show that, in math during third term the gap between girls and boys blind score equals -0.041 points of the s.d, while it equals -0.147 during first term. This represents a relative improvement of girls compared to boys of 0.106 s.d. My results suggest that, in the absence of a gender bias, the achievement gap during third the term would have been equal to -0.130 instead of -0.041, therefore a relative improvement of girls of 0.017 instead of 0.106. Hence, in the absence of discrimination, girls would not have progressed more than boys during the 6th grade. The catching up we observe in math during the 6th grade is almost entirely driven by the positive effect of the gender discrimination on girls' progress. Following the same reasoning, it is easy to show that, over the long term, about half of girls catch-up of boys is caused by teachers' biased behavior in math[28].

4.5.3 Effect of teachers' biases on course choice

I finally test if teachers' biases in favor of girls affect the type of high school and courses they chose compared to boys. The 9th grade corresponds to the last grade of the lower (and compulsory)

[28] The calculus is as follows : the descriptive statistics presented in table 2 show that, in math at the end of the 9th grade, the achievement gap between girls and boys blind score equals +0.058 points of the s.d, while it is -0.147 at the beginning of the 6th grade. This represents a relative improvement of girls compared to boys of 0.205 points of the s.d. My estimates show that due to teachers' biases, girls' long term achievement relative to boys increase by 0.116 points of the s.d in math. This represents a little bit more than half of girls' total relative progress.

secondary school. After this grade, pupils can chose between a vocational, technical or general high school, the latter being chosen by the majority as it provides the most opportunities to continue studies at university. In our sample, 50.9% of the girls choose a general high school and 40.3% of boys. For the pupils who decided to attend a general high school, everyone attends the same courses during the 10th grade, but pupils have to specialize when they enter the 11th grade. Three options are available to them: sciences, humanities or economics and social sciences. In this sample, among girls in general high school, 32.8% chose the scientific course, while 40.2% of the boys did so. This reversal of the gender probability is striking as the scientific path is the most prestigious one, and the one that leads to higher education in science, technology, engineering and math (STEM) fields. These fields of studies are highly gender unbalanced in most countries. Therefore, it would be interesting to know if favoring girls is a mean to fight these persistent gender differences.

Using the same specification as before, I successively analyze the effect of teachers' discriminatory behavior during the 6th grade on three outcomes: girls' relative probability to attend a general highschool, to chose a scientific course and to repeat a grade. Results are presented in table 11. The dependent variable is the difference between girls and boys probability to attend a general highschool in grade 10 (columns 1 and 2), to chose a scientific course in grade 11 (columns 3 and 4) or to repeat one of the grades between grade 6 and grade 11 (columns 5 and 6).

First, I find that being assigned a teacher who favors girls in the 6th grade increases girls' relative probability to attend a general highschool (rather than a professional or technical one) by 0.15 percentage points when the discrimination is in a math course and 0.16 percentage points when the discrimination is in French. Knowing that on average in this sample, girls are 10.6% more likely than boys to attend a general highschool, the magnitude of the effect is very high : it multiplies by two girls higher probability than boys to chose a general highschool. This effect is however in line with Lavy and Sand (2015) who find that "the estimated effect of math teachers' stereotypical attitude [in favor of boys] on enrollment in advance studies in math is positive and significant for boys (0.093, SE=0.049) and negative and significant for girls (-0.073, SE=0.044)". This significant effect is also consistent with the preceding result on girls higher progress than boys until grade 9. The likelihood that a pupil attends a general highschool in grade 10 is highly correlated to his/her results at the end the lower secondary school (grade 9). Second, the results reported in columns 3 and 4 suggest that teachers' biases positively affect girls' relative probability to chose a scientific course during the 11th grade. As previously, this effect is observed whether the gender bias is in French (+0.095) or in math (+0.107). Although the coefficients are positive, it is interesting to notice that they are significantly lower than the preceding ones (on the probability to chose a general highschool). This observation is interesting because the scientific path is the most prestigious one, and the one that leads to higher

education in STEM fields. Although rewarding girls make them progress more (compared to boys) and attend more general highschool, this suggests that girls still face barriers that prevent them from increasing in the same proportion their likelihood to chose scientific courses. I am not able to provide evidence on the existence of such barriers, but recent papers show that low-income students are less likely to apply to prestigious and high-achieving college, hence creating an academic "undermatch"[29]. Since 68% of the pupils in this sample have low SES parents, this mechanism is relatively plausible. Finally, teachers' biased behavior slightly decreases girls relative probability to repeat a grade in math, but not in French.

All together, the positive effect of teachers biases on both girls' relative progress and schooling decisions is consistent with different mechanisms mentioned in prior literature. Firstly, positively rewarding girls can reduce the stereotype threat effect. In situations where stereotypes are perceived as important, some girls have been proved to perform poorly for the sole reason that they fear confirming the stereotypes (Spencer et al. 1999). If math is perceived by girls as more affected by teachers' stereotypes, over-grading girls in this subject can reduce their anxiety to be judged as poor performers, and therefore favor their progress. Over the short term, the fact that biases affect girls' relative progress in math but not in French is consistent with a reduction of the stereotype threat, which might be more prevalent in math than in French. My findings are also consistent with prior research highlighting a 'contrast effect' according to which a student's academic self-concept is positively influenced by his or her individual achievement, but negatively affected by other peers-average achievement - usually composed of peers in the classrooms - once controlled for individual achievement (Trautwein et al. 2006, Marsh and Craven, 1997). With regard to this contrast effect, giving higher grades to girls would have a twofold effect: from an absolute point of view, higher grades will positively affect girls' self-concept, and self-confidence in math, and from a relative point of view, girls' higher grades compared to boys will reduce the achievement gap between boys and girls, and therefore increase girls relative academic self-concept. Finally, my result tends to challenge Mechtenberg's (2009) theoretical predictions according to which girls are reluctant to internalize good grades in math, because they believe their grades are biased.

5 Conclusion

In most OECD countries, at the earliest stage of schooling, boys outperform girls in mathematics, but they underperform in humanities. Then over the school years, this achievement gap tends to vanish in math but persist in French. This paper studies how teachers biased grades can explain both the achievement gap between boys and girls and its evolution over time. I use data containing both blind and non-blind scores at different periods in time to identify, first the effect of teachers' stereotypes on their grades, and second the effect of biased rewards on pupils' progress and course choice. Firstly regarding discrimination, my results suggest that an impor-

[29] See for instance Hoxby and Avery 2013, Smith et al. 2013, Dillon et al. 2013.

tant positive discrimination exists in math towards girls, while no bias is observed in French. This gender bias cannot be explained by girls' better behavior than boys. However it partially captures girls' initial lower achievement in math. Regarding the impact of discrimination on girls' progress relative to boys, I observe that classes in which teachers present a high degree of discrimination in favor of girls during the 6th grade, are also classes in which girls tend to progress more compared to boys. This is true over the short and long term, hence suggesting a positive effect of rewards on girls' relative progress. Teachers' biases also affect girls relative likelihood to attend a general high school during the 10th grade (rather than a professional or technical one) and to choose a scientific course during grade 11. These results provide new empirical evidence on gender discrimination in grades and how it affects the gender achievement gap over the short term and long term.

I am however unable to disentangle the different channels through which a gender bias can affect girls' relative achievement. On the one hand, positively rewarding pupils could motivate them, make them increase their efforts, increase their self-confidence, and reduce the stereotype-threat they suffer from. On the other hand, if pupils consider effort and abilities as substitutes, a higher grade might be an incentive to reduce effort and work. Unfortunately, I am not able to disentangle these effects that might compensate or reinforce each other. This is an interesting question for future research. Another concern is the external validity of my results. In this study, I use a dataset that has been collected in schools of a relatively deprived educational district. This must be considered for issues of external validity of this analysis. Teachers assigned to deprived areas are on average younger than teachers in more advantaged schools, and we have seen that unexperienced teachers are more biased. Similarly, pupils in these areas might face more constraints (financial or self-censorship) regarding their schooling decisions.

Finally, this analysis provides several policy-relevant results regarding teachers grading. First, my findings suggest that marks given by teachers do not reflect only pupils' ability. They are affected by pupils' characteristics or attitudes. This raises the question of the relevance of some elements included in grades. Should a grade reflect a pupil's gender, his/her initial achievement, or behavior? The answer is not clear and seems to depend on the objective pursued. On the one hand, if grades are wished to measure only a pupil's ability, then the influence of a pupils' gender seems problematic, especially since several important decisions in school life are made on the basis of student grades (choice of stream at the beginning of upper secondary school, whether to repeat a year, choice of subject paths, etc). A simple and non-costly policy to remedy gender biases would consist of informing teachers about conscious or unconscious stereotyping and its potential effects on the grades that they give. French teachers have currently neither training nor information provided on the risks they face of judging their students through the lens of stereotypes. Making them aware of these risks might be a simple solution to significantly reduce biases in grades. Considering that teachers biases are problematic is also related to the ongoing debate on the use of grades as evaluation tools. The earlier teachers give grades to students, the higher the potential for discrimination. In several education systems,

pupils do not receive any grades before they turn 11 or more (Sweden for instance). On the other hand, grades could be considered as an instrument with which teachers improve student progress. In this case, teachers' grades could be a way to reduce the inequalities in achievement between boys and girls, by encouraging girls in math and boys in French to eliminate their lag.

References

[1] Bar, Talia, and Asaf Zussman. « Partisan grading ». American Economic Journal: Applied Economics 4, no 1 (2012): 30-48.

[2] Bénabou, Roland, and Jean Tirole. « Self-Confidence and Personal Motivation ». The Quarterly Journal of Economics 117, no 3 (8 janvier 2002): 871:915.

[3] Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. « How Much Should We Trust Differences-in-Differences Estimates? ». National Bureau of Economic Research Working Paper Series No. 8841 (2002).

[4] Blank, Rebecca M. « The Effects of Double-Blind versus Single-Blind Reviewing: Experimental Evidence from The American Economic Review ». The American Economic Review 81, no 5 (1 décembre 1991): 1041-67.

[5] Bonesrønning, Hans. « The effect of grading practices on gender differences in academic performance ». Bulletin of Economic Research 60, no 3 (2008): 245-64.

[6] Bouguen, Adrien. «Adjusting content to every students' needs : further evidence from a teacher training program». Ongoing research.

[7] Breda, Thomas, and Son Thierry Ly. « Do professors really perpetuate the gender gap in science? Evidence from a natural experiment in a French higher education institution ». CEP WP, june 2012.

[8] Burgess, Simon, and Ellen Greaves. « Test Scores, Subjective Assessment and Stereotyping of Ethnic Minorities ». Journal of Labor Economics 31, (2013): 535-576

[9] Cornwell, Christopher, David B. Mustard and Jessica Van Parys. « Noncognitive Skills and the Gender Disparities in Test Scores and Teacher Assessments: Evidence from Primary School ». J. Human Resources Winter 48, no 1 (2013): 236-264

[10] Crawford, Claire, Lorraine Dearden, and Costas Meghir. « When you are born matters: the impact of date of birth on child cognitive outcomes in England », octobre 2007.

[11] Dee, Thomas S. « A Teacher Like Me: Does Race, Ethnicity, or Gender Matter? ». American Economic Review 95, no 2 (2005): 158-65.

[12] ———. « Teachers and the Gender Gaps in Student Achievement ». The Journal of Human Resources 42, no 3 (1 juillet 2007): 528-54.

[13] Dillon, Eleanor Wiske and Jeffrey Andrew Smith. « The Determinants of Mismatch Between Students and Colleges ». NBER Working Paper no 19286 (August 2013).

[14] Else-Quest, Nicole M, Janet Shibley Hyde, and Marcia C Linn. « Cross-national patterns of gender differences in mathematics: a meta-analysis ». Psychological Bulletin 136, no 1 (janvier 2010): 103-27.

[15] Falch, Torberg, and Linn Renée Naper. « Educational evaluation schemes and gender gaps in student achievement ». Economics of Education Review 36 (octobre 2013): 12-25.

[16] Fennema, Elizabeth, Penelope L. Peterson, Thomas P. Carpenter, and Cheryl A. Lubinski. « Teachers' Attributions and Beliefs about Girls, Boys, and Mathematics ». Educational Studies in Mathematics 21, no 1 (1 février 1990): 55-69.

[17] Fryer, Roland G and Steven Levitt. « An Empirical Analysis of the Gender Gap in Mathematics ». American Economic Journal: Applied Economics, no 2 (2010): 210-40.

[18] Gneezy, Uri, Murial Niederle, and Aldo Rustichini. "Performance in competitive Environments: Gender Differences". Quarterly Journal of Economics, 118, no 3 (2003): 1049- 1074.

[19] Goldin, Claudia. « Notes on Women and the Undergraduate Economics Major. » CSWEP Newsletter, Summer 2013, 15 édition.

[20] Goldin, Claudia, and Cecilia Rouse. « Orchestrating Impartiality: The Impact of "Blind" Auditions on Female Musicians ». American Economic Review 90, no 4 (septembre 2000): 715-41.

[21] Hanna, Rema N. and Leigh L. Linden. « Discrimination in Grading ». American Economic Journal: Economic Policy 4, no 4 (2012): 146-168.

[22] Heckman, James J., Jora Stixrud, and Sergio Urzua. « The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior ». Journal of Labor Economics 24, no 3 (2006): 411-482.

[23] Hinnerich, Björn Tyrefors, Erik Höglin, and Magnus Johannesson. « Are boys discriminated in Swedish high schools? ». Economics of Education Review 30, no 4 (août 2011): 682-90.

[24] Hoff, Karla, and Priyanka Pandey. « Discrimination, Social Identity, and Durable Inequalities ». The American Economic Review 96, no 2 (1 mai 2006): 206-11.

[25] Hoxby, Caroline and Christopher Avery. « The Missing "One-Offs": The Hidden Supply of High-Achieving, Low-Income Students ». Brookings Papers on Economic Activity, (Spring 2013)

[26] Lavy, Victor. « Do gender stereotypes reduce girls' or boys' human capital outcomes? Evidence from a natural experiment ». Journal of Public Economics 92, no 10-11 (octobre 2008): 2083-2105.

[27] Lavy, Victor and Edith Sand. « On The Origins of Gender Human Capital Gaps: Short and Long Term Consequences of Teachers' Stereotypical Biases ». NBER Working Paper no 20909 (January 2015)

[28] Lindahl, Erica. « Does gender and ethnic background matter when teachers set school grades? Evidence from Sweden ». Uppsala University Working paper (2007).

[29] Machin, Stephen and Sandra McNally. « Gender and Student Achievement in English Schools », Oxford Review of Economic Policy no 21, (2005): 357-72.

[30] Machin, Stephen and Tuomas Pekkarinen. « Global Sex Differences in Test Score Variability », Science no 322, (2008): 1331-1332

[31] Marsh, Herbert. W., and Rhonda G. Craven. « Academic self-concept: Beyond the dustbowl. » In G. D. Phye (Ed.), Handbook of classroom assessment. San Diego, CA: Academic Press., 1997, 131:198.

[32] Marsh, Herbert W., and Rhonda G. Craven. « The Pivotal Role of Frames of Reference in Academic Self-Concept Formation: The Big Fish-Little Pond Effect », 2001.

[33] Mechtenberg, Lydia. « Cheap Talk in the Classroom: How Biased Grading at School Explains Gender Differences in Achievements, Career Choices and Wages ». Review of Economic Studies 76, no 4 (2009): 1431-59.

[34] Neblett, Enrique W, Cheri L Philip, Courtney D Cogburn, and Robert M Sellers. « African American Adolescents' Discrimination Experiences and Academic Achievement: Racial Socialization as a Cultural Compensatory and Protective Factor ». Journal of Black Psychology 32, no 2 (5 janvier 2006): 199-218.

[35] OECD. PISA 2009 Results: What Students Know and Can Do – Student Performance in Reading, Mathematics and Science, 2010.

[36] Ouazad, Amine, and Lionel Page. « Students' Perceptions of Teacher Biases: Experimental Economics in Schools ». Journal of Public Economics 105 (2013): 116-130.

[37] Ready, Douglas D., and David L. Wright. « Accuracy and Inaccuracy in Teachers' Perceptions of Young Children's Cognitive Abilities ». American Educational Research Journal 48, no 2 (1 avril 2011): 335-60.

[38] Robinson, Joseph Paul, and Sarah Theule Lubienski. « The Development of Gender Achievement Gaps in Mathematics and Reading During Elementary and Middle School Examining Direct Cognitive Assessments and Teacher Ratings ». American Educational Research Journal 48, no 2 (1 avril 2011): 268-302.

[39] Smith, Jonathan, Matea Pender and Jessica Howell. « The full extent of student-college academic undermatch ». Economics of Education Review 32, (February 2013): 247-261.

[40] Spencer, Steven J., Claude M. Steele, and Diane M. Quinn. « Stereotype Threat and Women's Math Performance ». Journal of Experimental Social Psychology 35, no 1 (janvier 1999): 4-28.

[41] Steele, Claude M., and Joshua Aronson. « Stereotype threat and the intellectual test performance of African Americans ». Journal of Personality and Social Psychology 69, no 5 (1995): 797-811.

[42] Tiedemann, Joachim. « Gender related beliefs of teachers in elementary school mathematics ». Educational Studies in Mathematics 41 (2000): 191-207.

[43] ———. « Teachers' Gender Stereotypes as Determinants of Teacher Perceptions in Elementary School Mathematics ». Educational Studies in Mathematics 50, no 1 (2002): 49-62.

[44] Trautwein, Ulrich, Oliver Ludtke, Herbert W. Marsh, Olaf Koller, and Jurgen Baumert. « Tracking, Grading, and Student Motivation: Using Group Composition and Status to Predict Self-Concept and Interest in Ninth-Grade Mathematics ». Journal of Educational Psychology 98, no 4 (novembre 2006): 788-806.

[45] Van Ewijk, Reyn. « Same Work, Lower Grade? Student Ethnicity and Teachers' Subjective Assessments ». Economics of Education Review 30, no 5 (octobre 2011): 1045-58.

[46] Wei, Thomas E. « Stereotype threat, gender, and math performance: evidence from the national assesment of educational progress ». Working Paper, Harvard University, 2009.

Table 1: Descriptive statistics and balance check of the attrition

	Full Sample	**Sample with no missing**	**Sample with missing**		
	Mean	Mean	Mean	Difference	p-value
Variables	(1)	(2)	(3)	(4)=(3)-(2)	
Test scores					
Blind t1 - French	-0.000	0.013	-0.270	-0.283***	(0.000)
Blind t1 - Math	0.000	0.011	-0.240	-0.251***	(0.000)
Non-Blind t1 - French	0.000	0.021	-0.426	-0.447***	(0.000)
Non-Blind t1 - Math	-0.000	0.018	-0.335	-0.354***	(0.000)
Pupils' characteristics					
% Girls	0.481	0.490	0.411	-0.079***	(0.000)
% Grade repetition	0.062	0.054	0.118	0.063***	(0.000)
% Disciplinary warning	0.062	0.061	0.077	0.016***	(0.000)
% Excluded from class	0.056	0.052	0.089	0.037***	(0.000)
% Temporary exclusion from school	0.036	0.038	0.020	-0.018***	(0.000)
Parents' characteristics					
% High SES	0.178	0.182	0.143	-0.040***	(0.000)
% Low SES	0.686	0.699	0.589	-0.109***	(0.000)
% Unemployed	0.117	0.109	0.181	0.072***	(0.000)
Teachers' characteristics					
% Female teachers - Math	0.499	0.492	0.551	0.059***	(0.000)
% Female teachers - French	0.846	0.848	0.829	-0.019***	(0.000)
Teachers' age - Math	34.378	34.240	35.407	1.167***	(0.000)
Teachers' age - French	37.942	38.235	35.748	-2.487***	(0.000)
Number of observations	4490	3964	526		

† Notes: Stars correspond to the following p-values: * p<.05; ** p<.01; *** p<.001. The full sample contains 4490 pupils. The sample with no missing scores during first term contains 3964 pupils. 526 observations are considered as missing since one test score at least is missing during first term.
This table presents the differences between the sample with no test score missing and the sample with missing scores. The fourth column "Difference" reports the coefficients of the regression of various dependent variables on a dummy indicating that the pupil has a score missing. All scores are standardized. Standard errors are robust. Parent's profession: Parents belong to the category high SES if they belong to the French administrative category "corporate manager" or "executive". Parents are classified as low SES if they belong to the categories "worker" or "white-collar worker". For both variables, the dummy takes the value 1 if at least one of the parents belongs to the category.

Table 2: Comparison between boys' and girls' test scores

			Girls		Boys			
			# obs	Mean	# obs	Mean	Diff	p-value
Score	**Period**	**Subject**		(1)		(2)	(3)=(1)-(2)	
Blind	Grade 6 - t1	Mathematic	2020	-0.075	2127	0.072	-0.147***	(0.000)
		French	2022	0.223	2135	-0.211	0.434***	(0.000)
	Grade 6 - t3	Mathematic	1754	-0.021	1804	0.020	-0.041***	(0.000)
		French	1761	0.202	1814	-0.196	0.398***	(0.000)
	Grade 9	Mathematic	1828	0.029	1781	-0.029	0.058***	(0.000)
		French	1841	0.223	1799	-0.228	0.451***	(0.000)
Non-Blind	Grade 6 - t1	Mathematic	2042	0.087	2140	-0.083	0.170***	(0.000)
		French	2024	0.236	2134	-0.224	0.460***	(0.000)
	Grade 6 - t3	Mathematic	2029	0.112	2127	-0.107	0.218***	(0.000)
		French	2008	0.234	2104	-0.224	0.458***	(0.000)

† Notes: All tests scores are standardized. Column (1) displays mean scores of girls in mathematics and French, by nature of grading (blind scores at the top and non-blind scores at the bottom), and by period (successively : first term of 6th grade, third term of 6th grade and 9th grade). Column (2) presents the same results for boys. Column (3) corresponds to the differences between girls' and boys' scores.

Distribution of Blind and Non-Blind scores (Grade 6 - t1) – **French**

Figure 1: Blind score

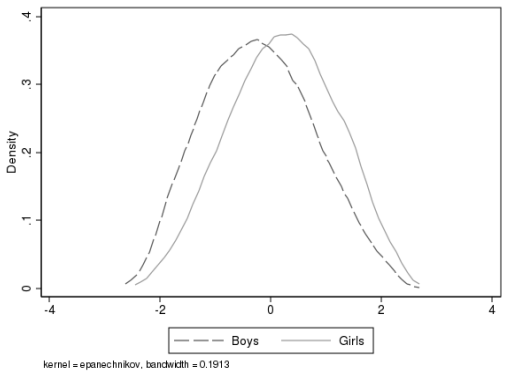
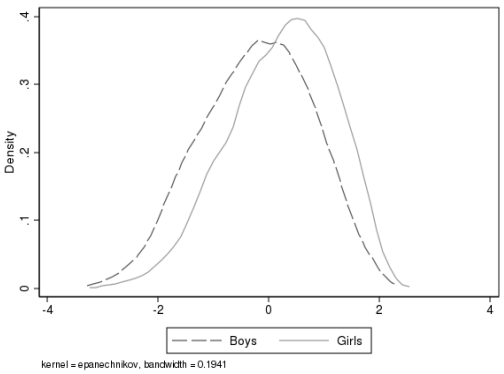


Figure 2: Non-Blind score



Distribution of Blind and Non-Blind scores (Grade 6 - t1) – **Math**

Figure 3: Blind score

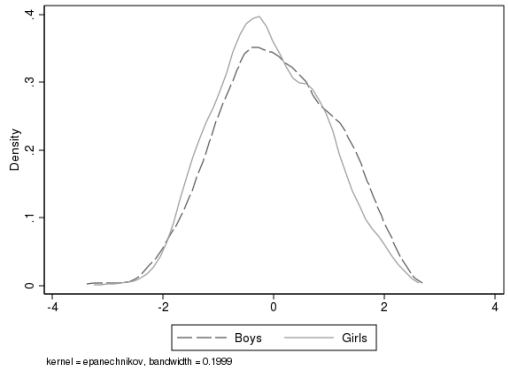
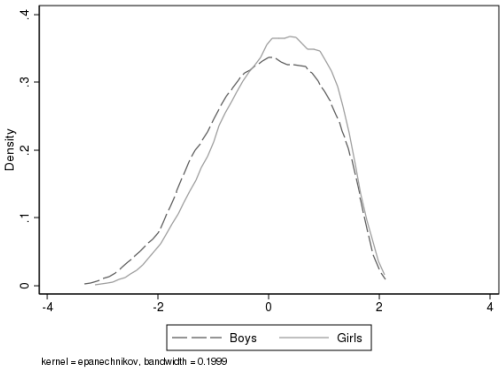


Figure 4: Non-Blind score



Evolution of the distribution of Blind scores – **French**

Figure 5: Grade 6 - t1

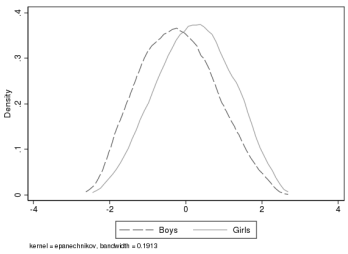


Figure 6: Grade 6 - t3

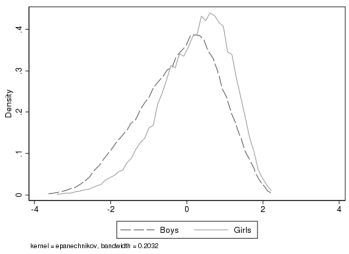
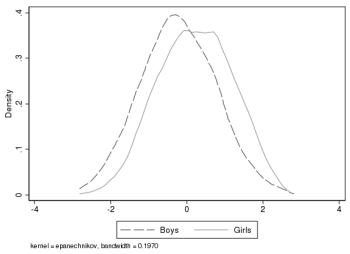


Figure 7: Grade 9



Evolution of the distribution of Blind scores – **Math**

Figure 8: Grade 6 - t1

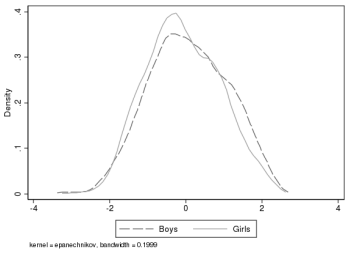


Figure 9: Grade 6 - t3

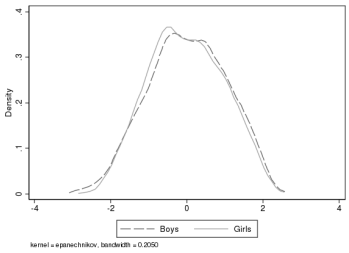


Figure 10: Grade 9

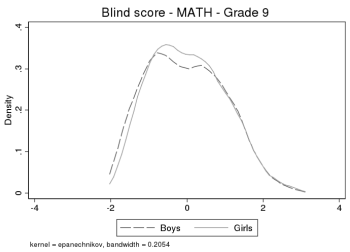


Table 3: Estimation of the gender bias using Double-Differences

	Balanced Sample		Full sample	
	Math	French	Math	French
Dep var : Scores				
Girls	-0.164***	0.411***	-0.152***	0.426***
	(0.028)	(0.019)	(0.028)	(0.018)
Non-Blind Score	-0.153**	-0.019	-0.156**	-0.011
	(0.053)	(0.045)	(0.052)	(0.045)
Girl x Non-Blind	0.323***	0.043	0.318***	0.027
	(0.026)	(0.031)	(0.027)	(0.032)
Constant	4.740***	3.672***	2.361***	0.450***
	(0.045)	(0.027)	(0.133)	(0.117)
Class FE	Yes	Yes	Yes	Yes
R2	0.116	0.159	0.118	0.158
Number of observations	8136	8116	8329	8315

Notes: The dependent variable is the score (both blind and non-blind) obtained by a pupil in French or math during the first term. Standard-errors are in parentheses and have been estimated with school level clusters. Stars correspond to the following p-values: * p<.05; ** p<.01; *** p<.001.
Each pupil has two observations: one for the blind score and one for the non-blind. The balanced sample contains 4068 pupils in math and 4058 in French for which both the blind and non-blind scores are non-missing. The full sample contains 4519 pupils. Some of them do not have two observations if the blind or non-blind score is missing.

Table 4: Double-Differences with control variables for pupils' characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var : Math scores						
Girls	-0.146**	-0.211***	-0.152***	-0.133***	-0.086**	-0.160***
	(0.040)	(0.039)	(0.028)	(0.027)	(0.027)	(0.028)
Non-Blind Score	-0.170*	-0.147*	-0.156**	-0.191**	-0.148*	-0.150**
	(0.064)	(0.067)	(0.052)	(0.054)	(0.057)	(0.051)
Girl x Non-Blind	0.327***	0.317***	0.318***	0.294***	0.289***	0.313***
	(0.031)	(0.029)	(0.027)	(0.027)	(0.029)	(0.027)
Controls for punishment		.				
Punishment		-0.566***				
		(0.076)				
Punishment x Non-Blind		-0.153*				
		(0.071)				
Punishment x Non-Blind x Girl		-0.301				
		(0.157)				
Controls for initial achievement				.	.	
Decile 1				-1.625***	-1.465***	
				(0.039)	(0.040)	
Decile 1 x Non-Blind				0.248***	0.229***	
				(0.059)	(0.060)	
Decile 1 x Non-Blind x Girl				0.245***	0.203**	
				(0.067)	(0.067)	
Decile 10					1.491***	
					(0.028)	
Decile 10 x Non-Blind					-0.331***	
					(0.036)	
Decile 10 x Non-Blind x Girl					-0.019	
					(0.050)	
Controls for grade repetition						.
Grade repetition						-0.352***
						(0.090)
Repetition x Non-Blind						-0.076
						(0.133)
Repetition x Non-Blind x Girl						0.077
						(0.112)
Constant	4.717***	5.034***	2.361***	2.631***	1.853***	2.492***
	(0.062)	(0.067)	(0.133)	(0.134)	(0.138)	(0.127)
Class FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.105	0.136	0.118	0.313	0.461	0.125
Number of observations	4413	4413	8329	8329	8329	8329

Notes: Standard-errors are in parentheses and have been estimated with school level clusters. Stars correspond to the following p-values: * p<.05; ** p<.01; *** p<.001. The dependent variable is the score (both blind and non-blind) obtained by a pupil in math during first term. The full sample is used in columns 3 to 5. The sample used in columns 1 and 2 is the full sample, to which pupils for which a punishment variable is missing have been removed.

Table 5: Estimation of the gender bias with pupils' rank as dependant vaariable

	Math	French
Dep var : Ranks		
Girls	1.193***	-2.806***
	(0.204)	(0.179)
Non-Blind Score	1.289***	0.339**
	(0.101)	(0.110)
Girl x Non-Blind	-2.247***	-0.430*
	(0.177)	(0.175)
Constant	2.521***	-4.617***
	(0.241)	(0.141)
Class FE	Yes	Yes
R2	0.048	0.091
Number of observations	8329	8315

Notes: The dependent variable is the rank (both blind and non-blind) of a pupil in math during first term. Standard-errors are in parentheses and have been estimated with school level clusters. Stars correspond to the following p-values: * p<.05; ** p<.01; *** p<.001. All tests scores are standardized.

Table 6: Comparison of DiD estimates of the gender bias for first and last term

	Math	French
	(1)	(2)
Coef Girl*Non-Blind	0.318	0.027
First term	(0.027)	(0.032)
Coef Girl*Non-Blind	0.259	0.064
Last term	(0.035)	(0.040)

Table 7: Evolution of test scores between the first term of grade 6 and later periods

			Grade 6 - t1		Later period			
			# obs	Mean	# obs	Mean	Diff	t-stat
Later period	**Subject**	**Gender**		(1)		(2)	(3)=(2)-(1)	
Grade 6 - t3	Mathematic	Girls	2020	-0.075	1754	-0.021	0.054	1.717
		Boys	2127	0.072	1804	0.020	-0.051	-1.563
	French	Girls	2022	0.223	1761	0.202	-0.021	-0.674
		Boys	2135	-0.211	1814	-0.196	0.015	0.458
Grade 9	Mathematic	Girls	2020	-0.075	1828	0.029	0.104	3.311
		Boys	2127	0.072	1781	-0.029	-0.101	-3.068
	French	Girls	2022	0.223	1841	0.223	0.000	0.011
		Boys	2135	-0.211	1799	-0.228	-0.017	-0.552

† Note: All tests scores are standardized. Column (1) presents the mean blind score obtained by boys and girls during the first term of 6th grade. Column (2) presents the mean blind scores during a later period (third term of 6th grade or 9th grade). Column (3) is the difference between the second column and the first column.

Boys and girls' progress over the 6th grade

Figure 11: French

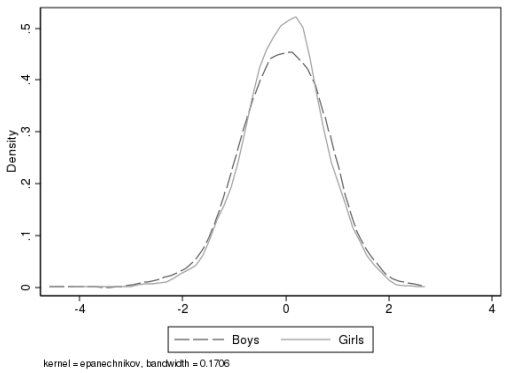
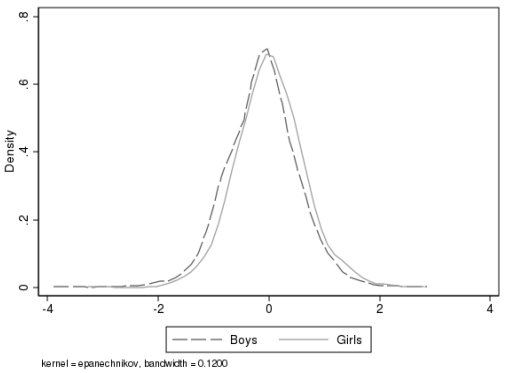


Figure 12: Math



Boys and girls' progress over the entire lower secondary school

Figure 13: French

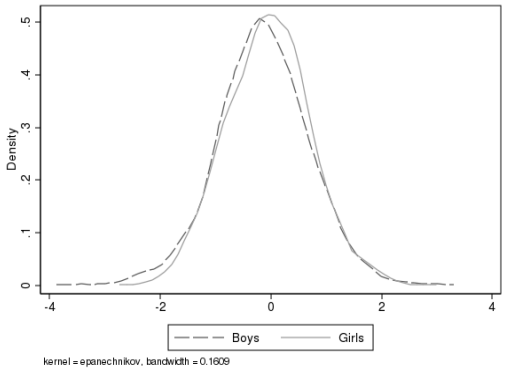
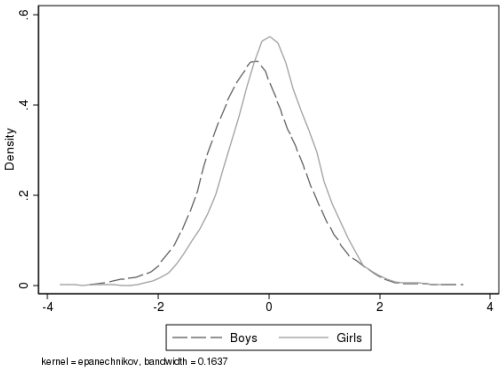


Figure 14: Math



Correlation between teachers' gender bias and girls' relative progress during the 6th grade.

Figure 15: French

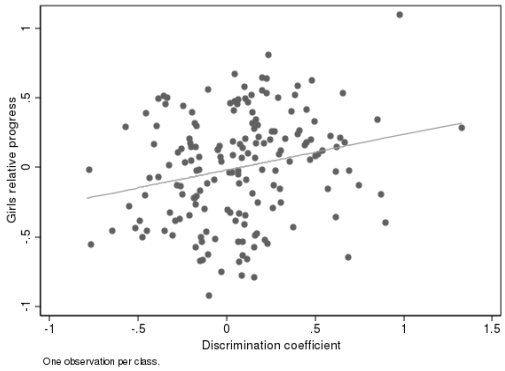


Figure 16: Math

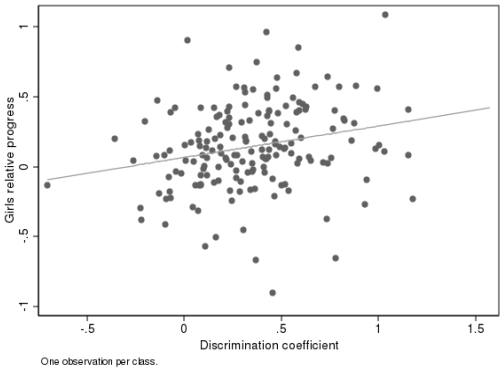


Table 8: Balance check of the attrition at the class level

	Grade 6 - t3		Grade 9		Grade 11	
	Math	French	Math	French	Math	French
Dep var: Class missing						
Discrimination	0.041	-0.001	0.043	0.006	0.058	0.016
	(0.085)	(0.066)	(0.062)	(0.018)	(0.055)	(0.016)
Number of observations	189	189	189	189	189	189

† Notes: Stars correspond to the following p-values: * p<.05; ** p<.01; *** p<.001. One observation per class. In columns 1 and 2, the dependent variable is a dummy equal to one if all blind scores are missing in a class at the end of grade 6. In columns 3 and 4, the dummy equals one if the blind score at the end of the 9th grade are missing. In columns 5 and 6, the dependent variable is a dummy equal to one if a pupil's course choice during the 11th grade is missing. The difference between column 5 and 6 lies in the subject affected by discrimination (math in column 5 and French in column 6). Robust standard-errors.

Table 9: Balance check of the attrition for boys and girls

	Grade 6 - t3		Grade 9		Grade 11	
	Math	French	Math	French	Math	French
Dep var: % girls missing						
Discrimination	0.028	-0.010	0.010	0.004	0.073	-0.004
	(0.080)	(0.066)	(0.044)	(0.038)	(0.056)	(0.042)
Dep var: % boys missing						
Discrimination	0.064	0.077	0.110*	0.059	0.005	0.051
	(0.073)	(0.062)	(0.051)	(0.032)	(0.028)	(0.030)
Number of observations	189	189	189	189	189	189

† Notes: Stars correspond to the following p-values: * p<.05; ** p<.01; *** p<.001. One observation per class. Respectively in the upper and bottom part of the table, the dependent variable corresponds to the percentage of girls (resp boys) with a missing score. In columns 1 and 2, the dependent variable is the percentage of girls (resp boys) for which the blind score is missing at the end of grade 6 (blind score missing in math in column 1 and French in column 2). In columns 3 and 4, the dependent variable is the percentage of girls (resp boys) for which the blind score is missing at the end the 9th grade. In columns 5 and 6, the dependent variable is the percentage of girls (resp boys) for which course choice during the 11th grade is missing. Robust standard-errors.

Table 10: Effect of the gender discrimination on girls' progress relative to boys

	Progress over 1 year		Progress over 4 years	
	Math	French	Math	French
Dep var : End of period $(B_G - B_B)_c$				
Gender bias - Grade 6 - t1	0.281**	0.169	0.375***	0.421***
	(0.079)	(0.100)	(0.093)	(0.091)
Gender achievement gap - Grade 6 - t1	0.878***	0.864***	0.611***	0.692***
	(0.065)	(0.113)	(0.057)	(0.066)
Constant	-0.010	0.025	0.029	0.141**
	(0.037)	(0.055)	(0.040)	(0.044)
R2	0.548	0.423	0.327	0.335
Number of observations	175	171	186	186

† Notes: The unit of observation is a class. In columns 1 and 2, the dependent variable is the gap between girls and boys third term blind score. In columns 3 and 4, the dependent variable is the gap between girls and boys score obtained at the end of the 9th grade national evaluation. The right hand side variable "Gender bias - Grade 6 - t1" corresponds to $[(NB_{1G} - B_{1G}) - (NB_{1B} - B_{1B})]_c$. The variable "Gender achievement gap - Grade 6 - t1" corresponds to $(B_{1G} - B_{1B})_c$. Standard-errors are in parentheses and have been estimated with school level clusters. Stars correspond to the following p-values: * p<.05; ** p<.01; *** p<.001. Regressions are weighted by class-size.

Table 11: Effect of the gender discrimination on girls' course choice and grade repetition relative to boys

	General training		Scientific course		Grade repetition	
	Math	French	Math	French	Math	French
Dep var : End of period $(Prob_G - Prob_B)_c$						
Gender bias - Grade 6 - t1	0.153**	0.163**	0.107**	0.095*	-0.097*	-0.061
	(0.044)	(0.048)	(0.031)	(0.040)	(0.038)	(0.040)
Gender achievement gap - Grade 6 - t1	0.233***	0.297***	0.166***	0.160***	-0.104**	-0.107*
	(0.035)	(0.036)	(0.026)	(0.028)	(0.035)	(0.041)
Constant	0.084**	-0.035	-0.014	-0.076***	-0.067***	-0.032
	(0.027)	(0.022)	(0.014)	(0.017)	(0.017)	(0.019)
R2	0.182	0.212	0.165	0.113	0.055	0.039
Number of observations	188	188	188	188	188	188

† Notes: The unit of observation is a class. In columns 1 and 2, the dependent variable is the gap between girls' and boys' probability to chose a general track from grade 10. In columns 3 and 4, the dependent variable is the gap between girls' and boys' probability to chose a scientific track in grade 11. In columns 5 and 6, the dependent variable is the gap between girls' and boys' probability to repeat a grade. The right hand side variable "Gender bias - Grade 6 - t1" corresponds to $[(NB_{1G} - B_{1G}) - (NB_{1B} - B_{1B})]_c$. The variable "Gender achievement gap - Grade 6 - t1" corresponds to $(B_{1G} - B_{1B})_c$. Standard-errors are in parentheses and have been estimated with school level clusters. Stars correspond to the following p-values: * p<.05; ** p<.01; *** p<.001. Regressions are weighted by class-size.

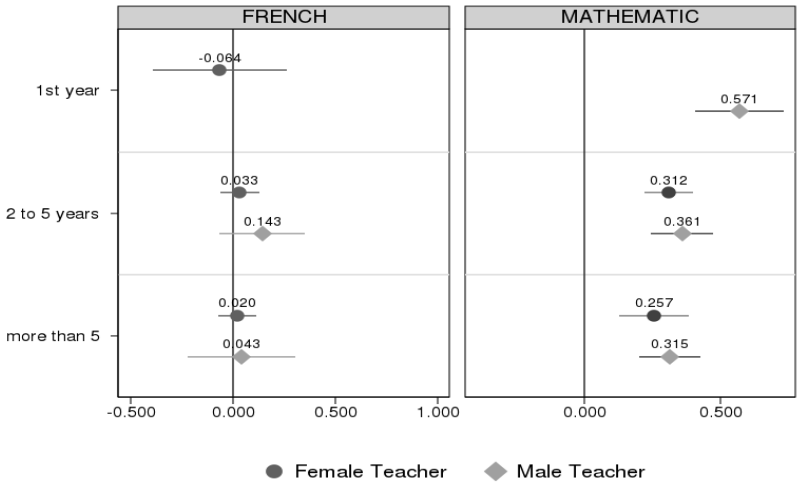
A Appendix

Do teachers' characteristics affect the gender bias ?

Contrary to prior research that find that girls tend to benefit from discrimination in all subjects (Lindhal 2007, Lavy 2008, Robinson and Lubienski 2011, Falch and Naper 2013, Cornwell et al. 2013), these results suggest that girls are favored only in math. To explain this difference, it is interesting to focus our attention on some characteristics of the teachers that could influence their grading practices, and that would be different for maths and French teachers. Both teachers' gender and their experience respect these two conditions. As displayed in table 1, while in math the share of men and women teachers is the same, the pattern is very different in French where 85% of the teachers are female. Similarly, math teachers are on average 3.5 years younger than French teachers.

Several studies show that the interplay between student and teacher gender plays a role in teachers' assessment (Dee 2005, Falch and Naper 2013, Lavy 2008, Ouazad and Page 2012, Lindhal 2007). To test if teachers' gender explain their discriminatory behavior, I run the previous DiD regressions separately on the sub-sample of male and female teachers. I find that teachers' gender has no effect on teachers discriminatory behavior in French, and a small and non significant difference in math. In this subject, female teachers' grades are less biased in favor of girls than male teachers' grades: the average gender bias equals 0.294 for women teachers and 0.343 for male teachers, but this difference is not significant[30]. These estimates decomposed by teachers experience are displayed in the graphic below.

Figure 17: Discrimination coefficient by teachers' gender and years of experience



[30]My findings are in line with Falch and Naper (2013) who find a limited or no effect of teachers' gender on the gender bias in grades. They do not confirm Lavy (2008) whose results suggest that all the gender bias in math is driven by male teachers.

Second, I test if teachers' experience affects the gender bias. To do so, I decompose the sample into three groups of teachers depending on their experience : first year of experience, two to five years, and more than five years. This focus on the first years of experience results from the young average age of the teachers in this sample: 58.1% of the math teachers have 5 or less years of experience, 45% for French teachers. I run the DiD regression on each of the three samples. The results suggest that in mathematics, teachers in their first year of teaching are more biased than more experienced teachers : the average gender bias represents 0.571 points of a s.d for new math teachers versus 0.295 for teachers with more than five years of experience. In French, teachers' experience has no effect on their gender biases.

B Appendix

Estimation of the gender bias if the blind and non-blind scores do not measure the same abilities.

In mathematical terms the assumption that both tests measure the same ability is equivalent to $\rho = 1$ and $v_i = 0$ in equation (3) defined in section 3.1: $\theta_{2i} = \rho\theta_{1i} + v_i$. If we release this hypothesis, we are back to the reduced form equation presented previously:

$$NB_i = \alpha_0 + \rho B_i + \alpha_2 G_i + (\epsilon_{iNB} + v_i - \rho\epsilon_{iB})$$

A way to test the validity of the hypothesis is to directly estimate the reduced form equation above and to verify if the coefficient ρ is significantly different from one. If not, both tests can be assumed to measure abilities which are perfectly correlated and DiD estimates can safely be assumed to be unbiased[31]. However to correctly estimate the parameter ρ in this equation, I have to get rid of the measurement error bias on B_i. Since B_i is a noisy measure of ability θ_{1i}, it is correlated to the measurement error ϵ_{iB}. I solve this endogeneity issue by instrumenting B_i. A pupil's month of birth is used as an instrument that is correlated to his/her blind score but independent from the error term.

In the literature, students' month of birth has been shown to be an important determinant of pupils' success at school (Crawford et al. 2007, Bedard and Dhuey 2006 and Grenet 2012). I test the correlation between blind scores and pupils' month of birth by running a regression of blind scores in French and math on a set of 11 dummies for each month of birth. January is taken as the reference month so that all coefficients should be interpreted relatively to this month. Figure 18 presents the correlation coefficients.

[31] I will discuss in a further section an additional assumption required for the DiD to be unbiased. Although we cannot test whether $v_i = 0$, the term v_i should be equally distributed between boys and girls.

Figure 18: Correlation between pupil's month of birth and the blind score.

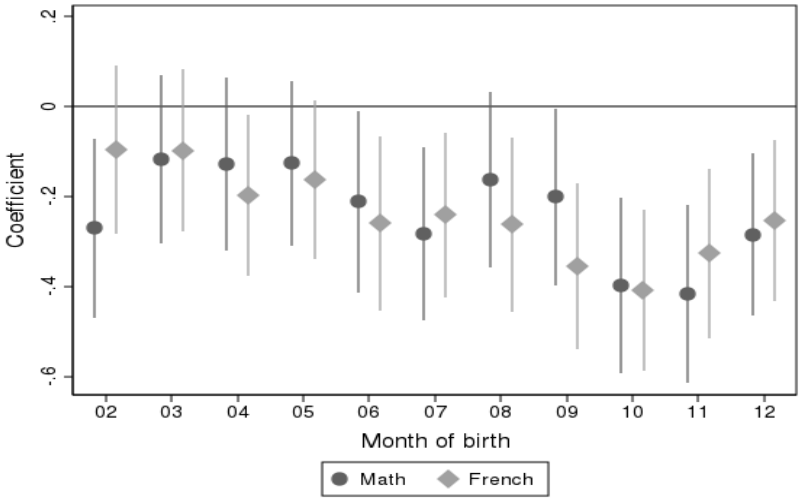


Table 12: First stage - Correlation between blind score and being born at the end of the year

	Math	French
Dep var : Blind t1		
Born End of Year	-0.150***	-0.173***
	(0.041)	(0.040)
Girl	-0.177***	0.386***
	(0.042)	(0.041)
Punishment	-0.469***	-0.522***
	(0.071)	(0.067)
Grade repetition	-0.323**	-0.204*
	(0.099)	(0.082)
High SES	0.410***	0.412***
	(0.055)	(0.053)
Constant	0.137***	-0.149***
	(0.039)	(0.038)
R2	0.060	0.112
Number of observations	2175	2127
F stat	14.12	18.01

Notes: The dependent variable is the blind score obtained by a pupil in during first term. Standard-errors are in parentheses. Stars correspond to the following p-values: * p<.05; ** p<.01; *** p<.001. All tests scores are standardized.

There is clear evidence that pupils born at the end of the year have lower results than

those born at the beginning of the year. From this observation, and to avoid including too many instrumental variables in the equation, I create dummy variable for pupils born after July. Results of the first stage regression are displayed in table 12. Once controlled for covariates, being born at the end of the year has an important negative effect on blind scores – 0,150 points of the s.d in math and 0,173 in French. The F-stat reported at the bottom of the table corresponds to the stat obtained when the blind score is regressed on the instrument only.

Being born at the end of the year will be a valid instrument if the following exclusion restriction holds: the only reason why a pupil's month of birth affects teachers' grades is because being born at the end of the year impacts his ability – measured by the blind score – once controlled for other covariates. In other words, being born at the end of the year is uncorrelated to the random shocks that enter the error term of equation (5): $\epsilon_{iNB} + v_i - \rho\epsilon_{iB}$. I claim this restriction is valid, provided that I control for pupils' behavior, parents' profession and grades retention, three variables that might be correlated to being born at the end of the year. The reduced form equation (5) is estimated, first with standard OLS, and second by instrumenting the blind score. Results are presented in table 13 and commented directly in the paper.[32]

Table 13: OLS and IV estimates of the reduced form

	OLS		IV	
	Math	French	Math	French
Dep var : Non-Blind score				
Blind score	0.760***	0.684***	1.090***	0.964***
	(0.019)	(0.031)	(0.100)	(0.099)
Girl	0.264***	0.172***	0.339***	0.080
	(0.028)	(0.043)	(0.032)	(0.057)
Constant	-4.794***	-9.031***	-7.617***	-11.585***
	(0.190)	(0.309)	(0.846)	(0.896)
Class FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
R2	0.687	0.607	0.594	0.549
Number of observations	2175	2127	2175	2127
p-val(Blind=1)			0.37	0.72

Notes: Standard-errors are in parentheses and have been estimated with school level clusters. Stars correspond to the following p-values : * p<.05; ** p<.01; *** p<.001. The unit of observation is a pupil. The sample contains 2175 pupils in math for which the blind score, non-blind score and punishment variable are non-missing, 2127 in French. The instrument is a dummy variable equal to one if a pupil is born between July and December.
Control variables included : grade repetition, punishment and high SES.

[32] As previously, all regressions include class fixed-effects. They are run on a sample that contains 2175 pupils in math for which the blind score, non-blind score and punishment variable are non-missing, and 2127 in French. Standard errors are estimated with school level clusters to take into account common shocks at the school level.

Finally, regarding the exclusion restriction, some might argue that once controlled for the abilities measured by the blind score, being born at the end of the year is not perfectly independent from unobserved specific skills v_i tested by the non-blind score only. If this is the case, it is likely that being born at the end of the year would also be negatively correlated with these unobserved skills. Therefore the IV estimates of ρ might be an upper bond for the true value of ρ, while the OLS would be a lower bound (due to the downward measurement error bias). Indeed, the IV estimate is $\rho_{IV} = \frac{Cov(NB_i, EndYear_i)}{Cov(B_i, EndYear_i)}$. If a correlation exists between v_i and being born at the end of the year, this would affect the numerator of the formula by increasing $Cov(NB_i, EndYear_i)$. Hence ρ_{IV} would be an upper bound for the parameter ρ.

C Appendix

Measure of the omitted variable bias affecting ρ and α_2.

Since girls perform initially lower than boys in mathematics, and higher in French, the blind score is correlated to a pupils' gender. The downward bias on ρ could affect the estimate of α_2. Using the formula of the omitted variable bias allows me to determine the direction of the bias that affects both ρ and α_2 (Bouguen, 2014).

The well-known formula of the omitted variable bias is :

$$E(b_1/X) = \beta_1 + (X_1'X_1)^{-1}X_1'X_2\beta_2 \tag{16}$$

where X_1 is a vector of the observed variables, X_2 is a vector of the unobserved variables, β_1 is the vector of the estimated coefficients of the observed variables, and β_2 is the vector of the coefficients of the unobserved variables.

In my setting, the observed variables are the blind score B_i and a pupil's gender G_i, and the unobserved variable is the error term affecting the blind score ϵ_{Bi} :

$$X_1 = \begin{pmatrix} B_1 & G_1 \\ B_2 & G_2 \\ \vdots & \vdots \\ B_n & G_n \end{pmatrix}, \beta_1 = \begin{pmatrix} \rho \\ \alpha_2 \end{pmatrix}, X_2 = \begin{pmatrix} \epsilon_{B,1} \\ \epsilon_{B,2} \\ \vdots \\ \epsilon_{B,n} \end{pmatrix}, \beta_2 = -\rho$$

In the following, I simplify notations as follows: $\sum_{i=1}^{N} = \sum$ and $\epsilon_{B_i} = \mathcal{E}_i$
Hence :

$$(X_1'X_1) = \begin{pmatrix} \sum B_i^2 & \sum B_iG_i \\ \sum B_iG_i & \sum G_i^2 \end{pmatrix}$$

$$(X_1'X_1)^{-1} = \frac{1}{\sum B_i^2 \sum G_i^2 - (\sum B_i G_i)^2} \begin{pmatrix} \sum G_i^2 & -\sum B_i G_i \\ -\sum B_i G_i & \sum B_i^2 \end{pmatrix}$$

$$(X_1'X_2) = \begin{pmatrix} \sum B_i \mathcal{E}_i \\ \sum G_i \mathcal{E}_i \end{pmatrix}$$

$$(X_1'X_1)^{-1}(X_1'X_2) = \frac{1}{\sum B_i^2 \sum G_i^2 - (\sum B_i G_i)^2} \begin{pmatrix} \sum G_i^2 \sum B_i \mathcal{E}_i - \sum B_i G_i \sum G_i \mathcal{E}_i \\ \sum B_i^2 \sum G_i \mathcal{E}_i - \sum B_i G_i \sum B_i \mathcal{E}_i \end{pmatrix}$$

$$(X_1'X_1)^{-1}(X_1'X_2)\beta_2 = \frac{1}{\sum B_i^2 \sum G_i^2 - (\sum B_i G_i)^2} \begin{pmatrix} -\rho \sum G_i^2 \sum B_i \mathcal{E}_i + \rho \sum B_i G_i \sum G_i \mathcal{E}_i \\ -\rho \sum B_i^2 \sum G_i \mathcal{E}_i + \rho \sum B_i G_i \sum B_i \mathcal{E}_i \end{pmatrix}$$

The first row gives the bias which affects the estimates of the coefficient of B_i. The second row corresponds to the bias on the coefficient α_2 of the variable G_i :

$$E(\hat{\alpha_2}) = \alpha_2 - \rho \frac{\sum B_i^2 \sum G_i \mathcal{E}_i - \sum B_i G_i \sum B_i \mathcal{E}_i}{\sum B_i^2 \sum G_i^2 - (\sum B_i G_i)^2} \tag{17}$$

Dividing both the numerator and denominator by n^2, gives :

$$E(\hat{\alpha_2}) = \alpha_2 - \rho \frac{V(B_i)Cov(G_i, \mathcal{E}_i) - Cov(B_i, G_i)Cov(B_i, \mathcal{E}_i)}{V(B_i)[V(G_i) - \bar{G_i}] - Cov(B_i, G_i)^2} \tag{18}$$

Dividing both the numerator and denominator by $V(B_i)V(G_i)\sigma_{\mathcal{E}_i}$ gives:

$$E(\hat{\alpha_2}) = \alpha_2 - \rho \frac{r_{(G_i,\mathcal{E}_i)} - r_{(G_i,B_i)}r_{(B_i,\mathcal{E}_i)}}{1 + \frac{\bar{G_i}}{V(B_i)} - r^2_{(B_i,G_i)}} \frac{\sigma_{\mathcal{E}_i}}{\sigma_{G_i}} \tag{19}$$

where $\sigma_{\mathcal{E}_i}$ is the standard deviation of $\mathcal{E}_i$, σ_{G_i} is the standard deviation of G_i, $r_{(G_i,\mathcal{E}_i)}$ is the correlation coefficient between G_i and $\mathcal{E}_i$, $r_{(B_i,\mathcal{E}_i)}$ is the correlation coefficient between B_i and $\mathcal{E}_i$ and $\bar{G_i}$ is the mean of the variable G_i.

Being a girl is assumed to be orthogonal to the shock affecting the blind score so that $r_{(G_i,\mathcal{E}_i)} = 0$:

$$E(\hat{\alpha_2}) = \alpha_2 + \rho \frac{r_{(G_i,B_i)}r_{(B_i,\mathcal{E}_i)}}{1 + \frac{\bar{G_i}}{V(B_i)} - r^2_{(B_i,G_i)}} \frac{\sigma_{\mathcal{E}_i}}{\sigma_{G_i}} \tag{20}$$

Based on this formula, the direction of the bias depends on the sign of each of its elements: ρ is the correlation coefficient between the blind score and the non-blind score. It is positive. By definition, standard deviation and variances are also positive, as is the average value of the dummy G_i. Finally, we can easily show that $r_{(B_i,\mathcal{E}_i)}$ is positive[33]. Hence, the direction of the bias

[33] In a standard measurement error model $r_{(B_i,\mathcal{E}_i)} = \frac{Cov(B_i,\mathcal{E}_i)}{\sigma_{B_i}\sigma_{\mathcal{E}_i}} = \frac{V(B_i)}{\sigma_{B_i}\sigma_{\mathcal{E}_i}} = \frac{\sigma_{\mathcal{E}_i}}{\sigma_{B_i}} > 0$

is fully determined by the sign of $r_{(G_i,B_i)}$. This is the correlation coefficient between G_i and B_i. It is positive in French, where girls perform higher than boys for the standardized evaluation, and negative in mathematics where they perform lower at the beginning of the 6th grade. This means that in math, the estimate of the coefficient $\hat{\alpha_2}$ is a lower bound for the true value of α_2. In French the estimate is an upper bound.

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

1340	Olivier Marie Ulf Zölitz	'High' Achievers? Cannabis Access and Academic Performance
1339	Terence C. Cheng Joan Costa-i-Font Nattavudh Powdthavee	Do You Have To Win It To Fix It? A Longitudinal Study of Lottery Winners and Their Health Care Demand
1338	Michael Amior	Why are Higher Skilled Workers More Mobile Geographically? The Role of the Job Surplus
1337	Misato Sato Antoine Dechezleprêtre	Asymmetric Industrial Energy Prices and International Trade
1336	Christos Genakos Svetoslav Danchev	Evaluating the Impact of Sunday Trading Deregulation
1335	Georg Graetz Guy Michaels	Robots at Work
1334	Claudia Steinwender	The Roles of Import Competition and Export Opportunities for Technical Change
1333	Javier Ortega Gregory Verdugo	The Impact of Immigration on the Local Labor Market Outcomes of Blue Collar Workers: Panel Data Evidence
1332	David Marsden	Teachers and Performance Pay in 2014: First Results of a Survey
1331	Andrea Tesei	Trust and Racial Income Inequality: Evidence from the U.S.
1330	Andy Feng Georg Graetz	Rise of the Machines: The Effects of Labor-Saving Innovations on Jobs and Wages

1329	Alex Bryson Andrew E. Clark Richard B. Freeman Colin P. Green	Share Capitalism and Worker Wellbeing
1328	Esther Hauk Javier Ortega	Schooling, Nation Building and Industrialization: A Gellnerian Approach
1327	Alex Bryson Rafael Gomez Tingting Zhang	All-Star or Benchwarmer? Relative Age, Cohort Size and Career Success in the NHL
1326	Stephan E. Maurer	Voting Behaviour and Public Employment in Nazi Germany
1325	Erik Eyster Kristof Madarasz Pascal Michaillat	Preferences for Fair Prices, Cursed Inferences, and the Nonneutrality of Money
1324	Joan Costa-Font Mireia Jofre-Bonet Julian Le Grand	Vertical Transmission of Overweight: Evidence From English Adoptees
1323	Martin Foureaux Koppensteiner Marco Manacorda	Violence and Birth Outcomes: Evidence From Homicides in Brazil
1322	Réka Juhász	Temporary Protection and Technology Adoption: Evidence from the Napoleonic Blockade
1321	Edward P. Lazear Kathryn L. Shaw Christopher Stanton	Making Do With Less: Working Harder During Recessions
1320	Alan Manning Amar Shanghavi	"American Idol" - 65 years of Admiration
1319	Felix Koenig Alan Manning Barbara Petrongolo	Reservation Wages and the Wage Flexibility Puzzle

The Centre for Economic Performance Publications Unit
Tel 020 7955 7673 Fax 020 7404 0612
Email info@cep.lse.ac.uk Web site http://cep.lse.ac.uk