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Ability to Sustain Test Performance and Remedial Education: Good News for Girls*

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Abstract

Growing evidence shows that skills other than cognitive are crucial to understand labor market and other outcomes in life and that these skills are more malleable than the cognitive ones at later ages. However, little is known about the role of education in improving these abilities for disadvantaged teenagers in developed countries. In this paper we address two questions: (i) Can educational interventions aimed at teenagers improve skills other than cognitive? (ii) Can we expect heterogeneous effects depending on the students' gender? We take advantage of a remedial education program for under-performing students implemented in Spain between 2005 and 2012, and, following recent literature, we consider testing and survey behaviors as measures of non-cognitive skills. We use external evaluations of the schools (PISA 2012) and exploit the variation in the question ordering of the test to compute students' ability to sustain performance throughout it. We find that the program had a positive effect on girls' ability to sustain test performance but no impact for boys.

Keywords: remedial education, test performance, program evaluation, PISA.

JEL classification numbers: H52, I23, I28, J24.

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1 Introduction

In skill acquisition both cognitive and non-cognitive abilities are relevant in explaining long-term outcomes such as high education investment and job market perspectives. As suggested by a growing body of the literature, skills other than cognitive are as crucial as cognitive skills in determining students' school achievements and in turn their educational choices.[1] Interestingly, recent literature documents the existence of a positive gender gap favoring girls in several measures of non-cognitive skills.[2] Moreover, and even more importantly for our study, as suggested by Carneiro and Heckman (2003), both cognitive and non-cognitive skills differ in their malleability over the life cycle, with the latter being more malleable than the former ones at later ages. Abilities other than cognitive can therefore be relevant when teenagers are involved in policy interventions such as remedial education programs, with lasting consequences in the long-term. However, the effect of remedial education programs on non-cognitive abilities and its possible heterogeneous effects have so far been rarely investigated.[3] This is precisely the aim of this paper. More specifically, we address the following questions: (i) Can educational interventions aimed at teenagers improve skills other than cognitive? (ii) Can we expect heterogeneous effects depending on the students' gender?

We provide evidence on these questions in Europe. We do so by taking advantage of two events. First, a multiyear program that offered remedial education for under-performing students from poor socioeconomic backgrounds, the Program for School Guidance (PAE), which was implemented in Spain between 2005 and 2012.[4] And second, the availability of non-self assessed measures of students' personality traits for a representative sample of Spanish adolescents in 2012. Similar to recent literature (see Balart et al. (2018), among others, and the review below), we use the term non-cognitive skills to describe the personal attributes not thought to be measured by IQ test or the like. We thus consider testing and survey behaviors, for instance decline in test performance, as measures of non-cognitive skills. Data on these measures are obtained from external evaluations of the schools, the PISA 2012 tests, and we exploit the variation in the question ordering of the test to compute students' sustained performance throughout it. Our study complements previous literature which focused on the impact of this

[1] See, among others, Heckman and Rubinstein (2001), Heckman et al. (2006), Cunha and Heckman (2008), Carneiro et al. (2007) or Lindqvist and Westman (2011).

[2] See for instance Jacob (2002), Cornwell et al. (2013) or Balart and Oosterveen (2018) and references therein.

[3] An important exception is Heckman (2000) who provide a review on interventions that took place in the nineties in the US.

[4] PAE is the Spanish acronym for Programa de Acompañamiento Escolar.

program on test scores (García-Pérez and Hidalgo-Hidalgo, 2017), that is, on skills much less flexible among teenagers. In addition, it adds to works on non-self assessed measures of non-cognitive skills by computing each student specific measure and analyzing whether a remedial intervention can improve these skills. Finally, it moves forwards the literature on gender gaps in education by studying whether girls are more apt to improve non-cognitive skills when joining these educational interventions.

Remedial education programs are designed to help poor-performing students to satisfy minimum academic standards. This is usually achieved by means of a targeted increase in instruction time combined with after-school individualized teaching in small study groups. These types of interventions are currently subject to increasing interest, especially in Europe as there is less of a tradition compared to U.S. where remedial education is quite widespread (see Carneiro and Heckman (2003) among others). However, policies targeting low-performing students are generally difficult to evaluate due to sample selection, as children with learning difficulties are not randomly assigned to programs. Students' individual and socioeconomic characteristics affect both their probability of being selected for the program and its success, when the selection mechanism is not completely observable. Only a few works address the identification problem and usually document the effectiveness of these programs in the short run. We comment below how this paper departs from previous works and contributes to the literature (see Section 2).

We compare skills in test taking of students who attended schools that participated in the PAE with the hypothetical outcomes that these same students would have obtained had they not attended PAE schools. The counterfactual outcomes are inferred using a control group composed of students in schools that did not join the PAE but participated in PISA 2012. To ensure that treatment and control groups are comparable on observables, students in the control group are re-weighted by assigning relatively more weight to those students whose individual, family and school characteristics are similar to those in the treated group.[5] Since we cannot observe whether a particular student is actually treated, to obtain a more precise estimation of the true effect of the program, we also decompose our evaluation sample and focus on students who are more likely to participate: those enrolled in schools with a high proportion of migrants and those whose parents have a low education level. In addition, we analyze whether the quality in the implementation of the program, measured by the number of students per teacher

[5]See also García-Pérez and Hidalgo-Hidalgo (2017) for the same empirical strategy or Hospido et al. (2015) who employ a similar approach to examine the impact of financial education program on student' scores.

in remedial classes, has a differential impact on our outcomes of interest. Finally, we replicate our main analysis using the school as unit of observation.

We find that educational interventions aimed at teenagers can improve their non-cognitive skills. In particular we show that the PAE has a substantial positive effect on our main measure of these type of skills (i.e. the student's ability to sustain test performance): it reduces the probability of falling behind into the bottom part of the ability to sustain test performance distribution by about 2 percentage points. The estimated increase on mean rate of decline in test performance is between 0.041 and 0.049 of one standard deviation. The corresponding figures (reduction in the probability of falling behind the bottom part and increase in mean rate) for girls are 4.6 percentage points and 0.1 of one standard deviation. We found no impact of the program on boys. Such result is not due to a larger proportion of girls in the percentiles of the outcome distribution where the impact of the program is larger, nor to a higher participation of girls to it, or to gender differences in test taking strategies. It might be explained by the fact that girls participate more intensively and they better respond to the remedial education activities in terms of non-cognitive skills. The estimated impact of the program for the subsample of students with higher chances of being treated (at schools with a high proportion of migrants) is similar in size to the impact for the whole sample of students, thus suggesting that we come close to estimate the true impact of the program when using the whole sample. Not surprisingly, students in schools where the program was better implemented (i.e. the student-teacher ratio in remedial classes is lower) benefit more from it, especially if they belong to the lowest quartile of the distribution. Finally, our results hold when we consider the school, instead of the student, as the unit of analysis.

The paper is organized as follows. Section 2 provides a summary of the related literature and how this paper contributes to it. Section 3 presents our measure of sustained test performance. Section 4 summarizes the remedial intervention program and presents the data and descriptive statistics used in the paper. Section 5 describes the methodology. Section 6 reports the overall results of the impact of the intervention. Section 7 provides results of its possible heterogeneous effects and discusses the validity of these findings. Section 8 concludes.

2 Brief literature review

Our paper contributes to three strands of the literature: the evaluation of remedial education programs, the research on non-cognitive skills and the literature on gender differences in both cognitive and non-cognitive skills. The first strand of literature studies the impact of remedial education programs mostly on students' cognitive skills. Lavy and Schlosser (2005) evaluate the short-term effects of the Bagrut 2001 program, a remedial intervention very close in spirit to the one proposed to be evaluated in this study, which provided additional instruction to underperforming high school students in Israel. Their results suggest that remedial education was more cost effective than alternatives based on financial incentives for pupils and teachers. Heckman (2000) provides a review on several interventions that operate during the adolescent years, in the nineties in the US. These programs were either mentoring type (The Big Brothers/Big Sisters (BB/BS) or the Philadelphia Futures Sponsor-A-Scholar (SAS)) or incentive-based activities promoting non-cognitive skills (Quantum Opportunity Program (QOP) or the Summer Training and Employment Program (STEP)). The review finds substantial evidence that mentoring and motivational programs oriented toward disadvantaged teenagers are effective. Therefore, it concludes that social policy should be more active in attempting to alter non-cognitive traits, especially in children from disadvantaged environments who receive poor discipline and little encouragement at home. Non-cognitive skills were also the objective of a remedial education program studied by Holmlund and Silva (2014). Such program targeted English secondary school pupils at risk of school exclusion and has been found to have little effect in helping treated youths to improve their age-16 test outcomes.[6] The most closely related papers to our are Battaglia and Lebedinski (2015) and García-Pérez and Hidalgo-Hidalgo (2017). The former analyzes the impact of the Roma Teaching Assistant program in Serbia, the main intervention targeting Roma inclusion in education in South Eastern Europe, on cognitive and non-cognitive skills. They find an overall positive effect of the remedial education program: children exposed to it are less absent from school. Moreover, first graders report lower dropout rates and better marks. García-Pérez and Hidalgo-Hidalgo (2017) analyze the same remedial program as in this paper but focus on cognitive skills, measured by PISA reading test scores. They find that PAE had a substantial positive effect on children's academic achievement and that a longer exposure

[6]Additionally, a number of recent papers have focused on remedial programs in tertiary education in Europe and the US. For example, De Paola and Scoppa (2014, 2015) analyze the impact of remedial courses on the achievement of college students in Italy. Bettinger and Long (2009) and Calcagno and Long (2008) study the causal effect of remediation on the outcomes of college students in Ohio and Florida, respectively.

to the program improves students' scores. The current paper departs from the previous work by studying the impact of this type of interventions on non-cognitive skills as measured by the ability to sustain the performance during the test. This allows to focus on abilities proved to be more likely affected by policy interventions at later stages of one persons' life, as remedial educational programs are. To the best of our knowledge, we provide novel evidence on the impact of educational interventions on non-cognitive skills aimed at teenagers in Europe.

This paper also relates to recent works on non-self assessed measures of non-cognitive skills. Borghans and Schils (2012) use the rate of decline in performance over the course of the 2006 PISA test's administration to measure non-cognitive factors such as agreeableness, motivation and ambition, and show that it is a good predictor of final levels of educational attainment, without being related to cognitive performance. Using 2009 PISA, Zamarro et al. (2016) expand the methods used by Borghans and Schils (2012) and find that the decline in test performance is a good predictor of international variation in test scores. Balart et al. (2018) decomposes the performance on the PISA test into two components: the starting level and the decline in performance during the test. The authors find that countries differ in the starting level and in the decline in performance, and that these differences are stable over time and positive and statistically significant associated with economic growth. Our paper complements their research by computing each student specific rate of decline during test performance instead of focusing on an aggregate measure at country level. In addition it studies whether remedial education programs can help to improve these skills.

Finally, we contribute to the literature on gender gap in education. Gender gaps in cognitive skills have long been studied by economists. The main finding is that, on average, girls perform better than boys in reading tasks whereas boys outperform girls in maths and science tasks (see Fryer and Levitt (2010), Cornwell et al. (2013) or, more recently, Nollenberger et al. (2016) and references therein). Most closely related to our paper, Balart and Oosterveen (2018) considers gender differences in non-cognitive skills as measured by performance during the test, and finds that the relative performance of girls improves as the test proceeds. This result is in line with findings in the literature that suggest that girls tend to perform better than boys in several measures of non-cognitive skills.[7] Our findings confirm these conclusions and move forward them by analyzing whether girls are not only better than boys in non-cognitive skills but also

[7] For instance, Jacob (2002) shows that girls have less behavioral problems and Cornwell et al. (2013) found that girls show more developed attitudes towards learning, etc.

more apt to improve them when receiving remedial education.

3 Ability to sustain test performance and the PISA test

Non-cognitive skills usually refer to work and study habits, such as motivation and discipline, and behavioral attributes, such as self-esteem and confidence (ter Weel, 2008; Holmlund and Silva, 2014). Often, such characteristics are self-assessed. Nevertheless, self-assessed measures might be biased by a lack of self-knowledge and subject to manipulation by students who can benefit from suggesting specific personality traits (see Sternberg et al. (2000), among others).

This evidence motivates the use of answering patterns to obtain measures of non-cognitive skills that do not rely on self-reports. We build on previous research (see e.g. Borghans and Schils (2012); Balart and Oosterveen (2018); Zamarro et al. (2016) mentioned above) which uses students' response patterns to surveys and tests to get a non-self assessed measure for their personality traits.[8] The idea is that students' test scores are not just the result of cognitive skills but also, and as doing the test takes time, the ability to sustain performance throughout it. Therefore, students, through their effort on tests and surveys, might provide some information about their conscientiousness, self-control or persistence. Building up on this notion, Borghans and Schils (2012) and, more recently, Balart et al. (2018) propose an approach to decompose students test scores into two elements: their initial performance and the decline in performance. The aim of this decomposition is precisely to generate two elements that capture both types of skills: whereas the initial performance provides a measure of cognitive skills, the performance decline is a measure of non-cognitive skills. The analysis of the latter is precisely the focus of this paper.[9] Of course, as Borghans et al. (2008) or Brunello et al. (2018) among others recognize, it is both conceptually and empirically very difficult to separate cognitive ability from non-cognitive skills. For instance, initial performance in a test might be influenced by non-cognitive abilities as motivation. To the extend that this is true, then by estimating the impact of the program on students' ability to sustain test performance we are underestimating its impact on non-cognitive skills.

Following recent literature, we therefore exploit the variation in the question ordering of

[8] In Section 6 below we also comment on results for students' self-assessed measures such as absenteeism and truancy, discipline measured by the way students behave in class, self-confidence, sense of belonging to the school, and perception of learning at schools.

[9] The comparison of the impact of the PAE on both cognitive and non-cognitive skills is out of the scope of this paper. Nevertheless, to complement our results here on non-cognitive skills, we also analyze the impact of the program on students' initial performance and final score. See comments on these results in Section 6.

a test to define our measure of non-cognitive skills: a student's sustained test performance. We computed it as the decline in performance throughout the PISA test, controlling for initial performance. We use microdata on each students' answer to every single administered question in PISA 2012 for Spain. Using both the codebooks and information provided by the OECD, we retrieve which question the student had to answer on each position of the test. As also acknowledged in the related literature, PISA tests have two characteristics that are crucial for investigating student's differences in performance during the test. First, PISA uses multiple test booklets with different orders for different subjects. Each booklet can contain four different clusters in three different subjects: maths, reading and science. Second, these booklets are randomly assigned to students (see OECD (2013)). This random assignment ensures that the variation in question numbers, that results from the ordering of clusters, is unrelated to characteristics of students.

As shown in Table 1, PISA 2012 has 13 different versions of the test (booklets), all of them containing four clusters of questions q (test items). A booklet contains approximately 50 to 60 test items. Each cluster of questions takes 30 minutes of test time and students are allowed a short break after one hour. Clusters labeled *Math 1, Math 2, Math 3, Math 4, Math 5, Math 6A and Math 7A* denote the seven paper-based standard mathematics clusters, *Reading 1* to *Reading 3* denote the paper-based reading clusters, and *Science 1* to *Science 3* denote the paper-based science clusters.[10] Each cluster appears in each of the four possible positions within a booklet once (OECD, 2013). This means that one specific test item appears in four different positions of four different booklets. For instance, cluster Maths 5 is included in booklets 1, 5, 9 and 11 as respectively the first, forth, third and second cluster. As it can be observed, the number of students that took each booklet is very similar and ranges from 813 to 884. Note also that each booklet is almost evenly shared by boys and girls. To construct our measure of student's individual rate of decline in test performance, we estimate the following specification for each student i:

[10]Balart and Oosterveen (2018) compare students' performance in the standard paper and pencil tests used in most PISA exams and the PISA 2015 test which was given on the computer and navigation across question units was restricted. The authors find no differences in students' test behaviors.

Table 1: Rotation design of the 13 PISA booklets

Booklet	Cluster 1	Cluster 2	Cluster 3	Cluster 4	# q	# q Math	# q Reading	# q Science	# Students	# Girls	# Boys
1	Math 5	Science 3	Math 6A	Science 2	60	25	-	35	875	457	418
2	Science 3	Reading 3	Math 7A	Reading 2	58	12	29	17	872	446	426
3	Reading 3	Math 6A	Science 1	Math 3	57	25	14	18	884	426	458
4	Math 6A	Math 7A	Reading 1	Math 4	52	37	15	-	871	445	426
5	Math 7A	Science 1	Math 1	Math 5	54	36	-	18	859	436	423
6	Math 1	Math 2	Reading 2	Math 6A	51	36	15	-	864	437	427
7	Math 2	Science 2	Math 3	Math 7A	53	35	-	18	875	454	421
8	Science 2	Reading 2	Math 4	Science 1	63	12	15	36	864	432	432
9	Reading 2	Math 3	Math 5	Reading 1	54	24	30	-	881	427	454
10	Math 3	Math 4	Science 3	Math 1	53	36	-	17	826	404	422
11	Math 4	Math 5	Reading 3	Math 2	49	35	14	-	822	424	398
12	Science 1	Reading 1	Math 2	Science 3	61	11	15	35	813	415	398
13	Reading 1	Math 1	Science 2	Reading 3	59	12	29	18	819	418	401

Source: PISA 2012

$$Pr(y_q) = \alpha_0 + \alpha_1 p_q + \alpha_2 d_q + u_q \tag{1}$$

where y_q is a dummy for whether student i answered question q correctly, p_q is the position of question q in the version of the test answered by student i and it is rescaled such that the first question is numbered as 0 and the last question as 1 and d_q is the difficulty of the question q (from simple choice to multiple choice or open question).[11] Our coefficient of interest is α_1 which shows the individual pattern of the test performance. A significant and negative (positive) coefficient would reveal a decline (improvement) in performance from the first to the last question of the test.[12] As our dependent variable is a dummy, we estimate a probit model. In addition to Equation (1) we estimate three comparable models for rate of decline in performance by considering the specific clusters of maths, reading, and science questions instead of the complete questionnaire in the PISA test.[13]

Figure 1 depicts the distribution of the pattern in performance (that is, the estimated coefficient α_1) during the test considering the complete questionnaire and the maths, reading and science clusters.

As can be observed, the majority of the students shows a decline in performance. The distribution of the pattern in performance is quite similar across the three subjects. However, the proportion of students with decline in performance in the maths and reading questionnaire seems larger than in the science questionnaire. Figure 2 reports average estimated rate of decline as in Equation (1) separately for boys and girls.

Several comments can be made from these figures. First, the average estimated pattern in performance is negative, in particular it is equal to -.097, which means that the probability to answer the last question correctly is 9.7 percentage points lower than the probability to

[11] As an alternative definition of correct answer, we recode a question as correct if the answer is correct or partially correct. We also provide two different measures of difficulty: (i) a dummy variable equal to 1 if it is a simple question and 0 otherwise and (ii) the percentage of students who correctly answer the question. See Section 6 for comments on robustness of our main results to these alternative definitions.

[12] Balart and Oosterveen (2018) also check for the non-linearity effect of the position of the question finding similar qualitative results than under the linear assumption.

[13] In addition, we consider of the number of items reached during the test as an alternative measure of student's non-cognitive skills. In particular it corresponds to the average last question answered by the student in each of the four clusters. Results on this measure are commented in Section 6 below.

Figure 1: Pattern in Performance

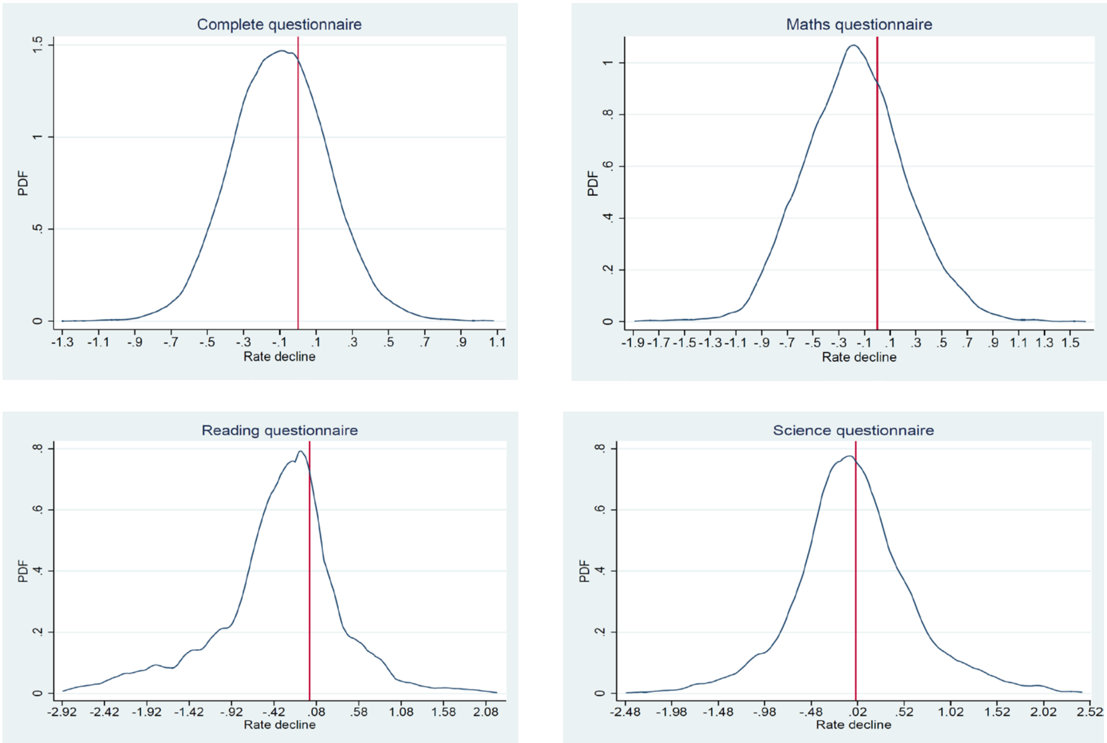
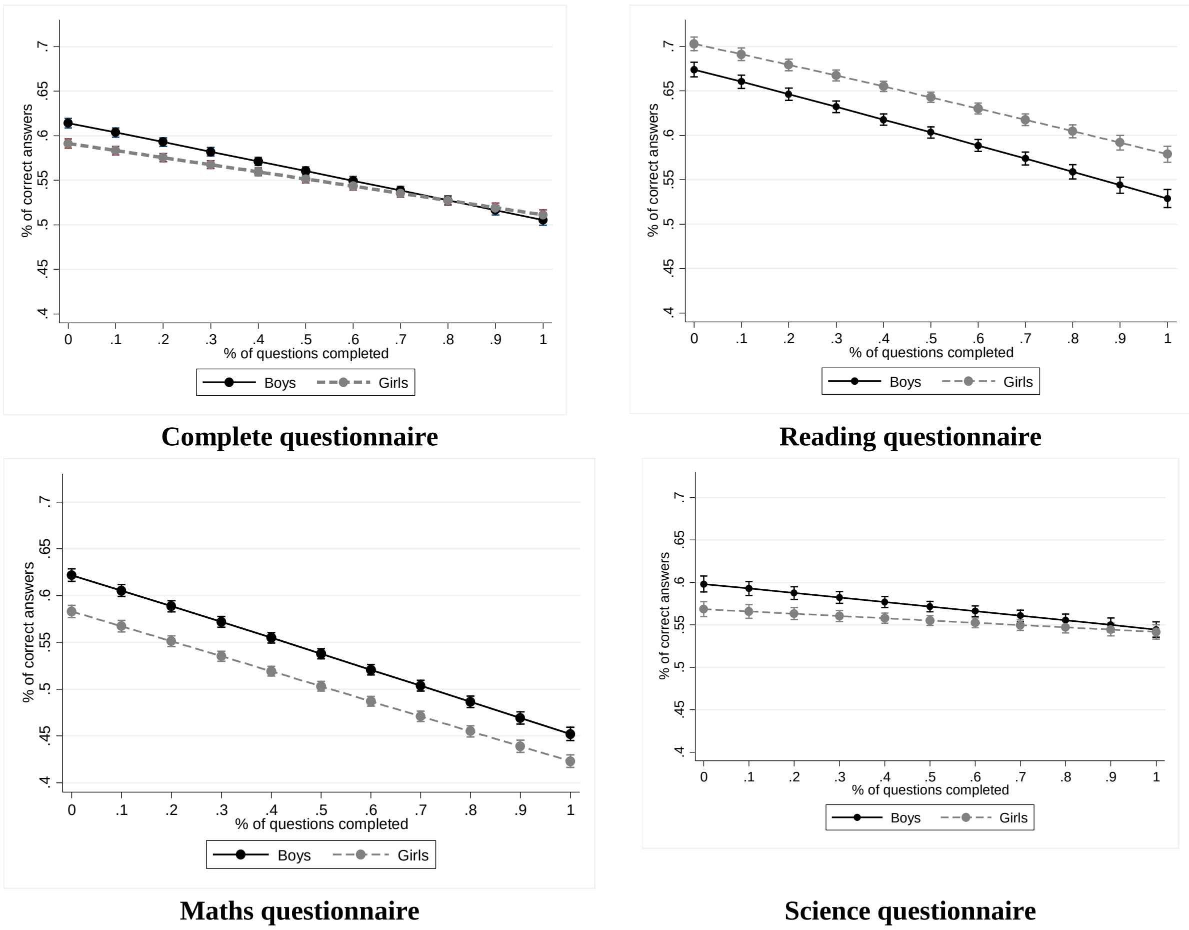


Figure 2: Pattern in Performance: The gender gap



answer the first question correctly. That is, there is a decline in performance during the test which confirm previous findings by Borghans and Schils (2012); Balart and Oosterveen (2018); Zamarro et al. (2016).[14] Therefore, from now on we refer to α_1 as the individual rate of decline. Second, the average estimated rate of decline is lower among girls, which is also in line with recent evidence by Balart and Oosterveen (2018) who find that girls have a higher ability to sustain performance. As it can be observed in the complete questionnaire, there is an initial gap in test scores favoring boys, however, during the test this advantage vanishes and girls finish the questionnaire outperforming boys. In the maths and science clusters boys outperform girls since the beginning of the test whereas girls score better than boys in the reading clusters. Finally, it can also be observed that in the maths and science clusters the initial gap favoring boys reduces with the progress of the test. In the reading clusters the initial gap favoring girls increases during the test.[15]

As the main goal of the PAE was to improve poor educational outcomes among students from disadvantaged backgrounds, we concentrate our analysis on the performance of that specific group of students. We define the group of *low achievers* by using the score in the first quartile of each rate of decline distribution (for the complete PISA test and the maths, reading and science clusters). Additionally, we also consider as an outcome variable the student's decline in test performance. Thus, in the rest of the paper we focus on the following two outcome variables: (i) each student's rate of decline; (ii) the probability of falling behind the general progress of the group or being a low achiever.

4 The remedial program

As mentioned above, Carneiro and Heckman (2003) and Heckman (2000) provide evidence that non-cognitive abilities are more likely than cognitive ones to be affected by policy interventions at later stages of one person's life and can therefore be relevant when teenagers are involved in a remedial education program (as it is in our case).

In providing further evidence on the impact of this type of interventions on non-cognitive skills we take advantage of a remedial program recently implemented in Spain, the PAE. The Program for School Guidance (PAE) is a program targeting public primary and secondary

[14] The drop in the percentage of correct answers from the first to the last cluster (56.23%, 55.55%, 54.06% and 51.84% for the first, second, third and fourth cluster respectively) constitutes additional evidence supporting the decline in performance during the test.

[15] All gender differences are statistically significant at 0.01 level.

schools. The aim of this intervention was to enhance the learning abilities and academic returns of underperforming students with poor socioeconomic backgrounds. This was pursued by stimulating reading habits, providing students with study organization techniques, and improving their social abilities. It consisted of providing support (at least 4 hours per week) during after-school hours to those students with special needs and learning difficulties. This support was provided in small groups of 5-10 students by instructors or teachers from the students' own schools. Students were selected by both their tutor and the rest of the teachers and could be in any grade within the school. They were chosen based on their poor academic results, general motivation and prospects, although there was no single quantifiable and explicit selection rule. During the remedial classes, the students engaged in guided reading and worked on the subjects that presented particular difficulties for them. Instructors offered clarification, provided additional materia and assisted students with work organization techniques.

The PAE was progressively introduced throughout the period 2005-2012. It provided support to public schools with a significant number of students from disadvantaged backgrounds. Even though PAE was implemented in both primary and secondary schools, we focus our analysis on secondary schools. The reason is that PISA 2012 exam is taken by 15-year-old students, with 10th grade being the reference grade for them. We focus here on the last four academic years the program was in place, that is, from 2008 till 2012, when students in our sample were in grades 7 to 10 and were attending the same secondary schools where they took the PISA exams. The reason is that, during the 2005-2008 period even if the secondary schools participated in the program, students in our sample did not benefit from it since they were still attending primary school.[16]

The intervention was jointly financed by both the central and the regional governments. The criteria to distribute funds for the program among regions included the number of public schools, the number of students attending public schools and the number of early school leavers or dropouts. Schools volunteered for the program and committed themselves to improve their students' outcomes by providing after-school instruction to those students with special needs. Unfortunately there is not an explicit percentage threshold of students from poor background required for the school to be admitted to the program. Nevertheless, apparently, the guidelines

[16]The Spanish education system is organized into three levels: primary (grades 1-6), secondary (grades 7-10) and pre-college (grades 11-12). The first two levels are compulsory (a student can choose to leave school at age 16). School starts at 6 years old. Most schools provide either primary or secondary and pre-college education. Only a very small sample of schools (most of them private) provide the three levels. See Spanish Ministry of Education (2016).

to distribute funds among schools within regions resemble the previous iterations. Bigger schools with an higher number of early leavers and dropouts were more likely to participate to the program.

As the program was implemented only in public schools, we exclude from the PISA database both private and private but publicly financed schools.[17] Following García-Pérez and Hidalgo-Hidalgo (2017), we do not consider in the analysis schools that joined other remedial programs or where the PAE was implemented during any academic year between 2005/06 and 2010/11 but not thereafter, i.e., during 2011/12, the year when the PISA exams were taken.[18] Our sample consists of 11,105 individuals from 395 schools, corresponding to 44% of the Spanish schools in PISA 2012 database of 902 schools.[19]

We consider as *treated* those students at schools that participated in the PAE during the same academic year in which PISA exams were taken, namely, 2011/12, regardless of whether the school joined the program before (that is, in any academic year between 2008/09 and 2010/11).[20] We consider as *controls* students in schools where the PAE was not implemented at all (that is, in no academic year between 2008/09 and 2011/12). As a result, there are 130 treated schools (with 3,694 students) and 265 control schools (with 7,411 students) in our sample.

4.1 Students' Characteristics

The PISA 2012 database provides microdata on each student's answer to each question, individual-level information on demographics (e.g., gender, immigration status, month and year of birth), socioeconomic background (parental education and occupation), school-level variables and achievement test scores in three disciplines: maths, reading and science.

Table 2 reports the main descriptive statistics of a set of individual, socioeconomic and

[17]We excluded 352 schools because they are private or private publicly financed schools.

[18]From the initial 550 public schools in PISA 2012 database we exclude 133 schools because they participated in other remedial programs and 22 schools where the PAE was implemented only before the academic year 2011/12.

[19]There are at most 35 students per school participating in PISA. These students are selected based on a two-stage sample design developed by the PISA program organizers. This selection ensured representation of the full target population of 15-year-old students in the participating countries. Only in a few cases, and with proper justification, PISA national project managers can exclude certain schools (e.g., in a remote geographical region) or students (e.g., special needs students). Nevertheless, the guidelines explicitly state that students must not to be excluded solely because of poor academic performance or normal discipline problems. See the PISA 2012 Technical Report for further details on PISA 2012 and García-Pérez and Hidalgo-Hidalgo (2017) for details on how the PAE was introduced in the schools.

[20]Alternatively we could analyze the effect of the program considering as treated those students in schools implementing the program for the first time in the academic year 2011/12. The low number of treated schools according to this definition (only 17) impedes from using the specification for the propensity score estimation adopted in the rest of estimations in the paper and thus results are not completely comparable.

school-level variables in our sample (in column (1)). It also reports descriptive statistics for the treated students (column (2)), control students (column (3)) and the differences between them (column (4)).

There are no statistically significant differences with respect to gender composition between the two groups. However, students in PAE schools differ from those in schools that did not join the program: control students are less likely to be migrants and are less likely to have repeated a grade. In addition, the proportion of educated parents and the index of educational materials are lower among treated students, suggesting that treated schools have a higher proportion of students from disadvantaged backgrounds. Treated and control students also differ regarding their initial test score, measured as the average test score in the first five questions of the first cluster of the test, which is statistically significantly lower among the former.[21] Finally, treated students came from larger sized schools that exhibited a larger proportion of dropouts and lower ESCS. Conversely, students in the control sample are from schools with a higher student-teacher ratio, where principal enhance school's reputation, parents exert less pressure on teachers and teachers contribute to a higher extent to create good school climate. They are also at schools with less migrants. In the analysis below, we comment on weighted control students in column (5) of Table 2 and on the difference between the treated and the weighted control group.

Table 3 shows the (standardized) estimated rate decline for the complete PISA test, for maths, reading and science. It reports the values by gender and overall. It also reports values for treated, controls and the weighted control group (see below). A negative (positive) rate of decline measures the % reduction (increase) in the probability of correctly answering a question as the position of that question increase 1% from the first to the last question.

Observe that, the percentage of boys in the *poorest skilled* group (first quartile of the rate decline distribution) is larger than the percentage of girls.[22] We comment on this later.

[21] We face a trade-off when selecting the number of questions considered as initial score. The larger is the number of questions, the lower the number of missings as students may jump some initial questions in the test. However, including many questions makes more difficult to assume that *initial score* is not capturing non-cognitive skills. As an approximation, we consider the first five questions.

[22] This result holds for the maths and science specific clusters (interestingly, those in which boys tend to perform

Table 2: Summary Statistics

Variable	(1) All	(2) Treated	(3) Controls	(4) P-value Diff. (2)-(3)	(5) Weighted Controls	(6) P-value Diff. (2)-(4)	(7) P-score
Individual variables							
Initial test score[a]	.621	.607	.628	.000	.606	.899	yes
	(.272)	(.274)	(.271)		(.277)		
Girl(=1)	.506	.499	.509	.312	.497	.829	yes
	(.5)	(.5)	(.5)		(.5)		
Migrant(=1)	.107	.149	.086	.000	.157	.276	yes
	(.309)	(.357)	(.281)		(.364)		
Repeated once(=1)	.237	.272	.22	.000	.271	.990	yes
	(.425)	(.445)	(.414)		(.445)		
Repeated more than once(=1)	.087	.106	.078	.000	.114	.189	yes
	(.282)	(.308)	(.268)		(.319)		
Attended kindergarden(=1)	.839	.83	.844	.054	.827	.705	yes
	(.367)	(.376)	(.363)		(.378)		
Socioeconomic variables							
Index of education possession[b]	.063	.041	.074	.068	.056	.425	yes
	(.885)	(.887)	(.885)		(.892)		
Mother highly educated(=1)[c]	.345	.303	.365	.000	.304	.982	yes
	(.475)	(.46)	(.482)		(.46)		
Father highly educated(=1)[d]	.33	.299	.346	.000	.3	.871	no
	(.47)	(.458)	(.476)		(.458)		
School variables							
School size	606.893	621.813	599.512	.000	627.463	.314	yes
	(318.336)	(278.108)	(336.328)		(278.614)		
Prop. of dropout	.095	.115	.085	.000	.117	.278	yes
	(.109)	(.111)	(.107)		(.118)		
Prob. of dropout in	.236	.308	.2	.000	.3	.411	yes
high quartile(=1)	(.425)	(.462)	(.4)		(.458)		
Prop. of migrants (school)	.107	.149	.086	.000	.121	.000	no
	(.122)	(.144)	(.103)		(.138)		
ESCS[e]	-.274	-.371	-.224	.000	-.37	.957	no
	(.977)	(.971)	(.974)		(.951)		
ESCS in high quartile(=1)	.272	.156	.329	.000	.159	.749	yes
	(.445)	(.363)	(.47)		(.366)		
Student-Teacher Ratio	9.621	9.264	9.798	.000	9.274	.825	yes
	(7.213)	(2.052)	(8.704)		(2.829)		
Principal enhance school's	.229	.223	.232	.263	.272	.000	no
reputation(=1)[f]	(.42)	(.416)	(.422)		(.445)		
Parental pressure on teachers(=1)[g]	.356	.391	.338	.000	.342	.000	no
	(.479)	(.478)	(.473)		(.474)		
School climate-teacher(=1)[h]	.564	.686	.504	.000	.691	.603	yes
	(.496)	(.464)	(.5)		(.462)		
Rural(=1)[i]	.42	.411	.424	.194	.428	.082	no
	(.494)	(.492)	(.494)		(.495)		
Observations	11,105	3,694	7,411		7,331		

Standard deviations in parentheses.
[a] Initial test score corresponds to the average score in the first five questions of the first cluster of the test.
[b] The index of education possession indicates whether the home possesses a desk and a quiet place to study, a computer and/or educational software and books to help with school work, and a dictionary. It ranges between -3.93 and 1.12.
[c] The mother is defined as highly educated if she has achieved at least tertiary education.
[d] The father is defined as highly educated if he has achieved at least tertiary education.
[e] Index of economic, social, and cultural status.
[f] The dummy is equal to 1 if the principal enhances school's reputation on weekly basis.
[g] The dummy is equal to 1 if the principal claims that parents exert pressure into teachers and principal to improve the school quality.
[h] It is a dummy equal to 1 if the school is below the median value of the index of teacher-related factors affecting school climate. Positive values indicate that the teacher-related behaviors hinder learning to a lesser extent. The index ranges between -3.2778 + 2.8533.
[i] It is a dummy equal to 1 if the school is located in a village or a small town.

Table 3: Students' outcomes: Rate decline

	Boys				Girls				Overall			
	All	Treated	Control	Weighted Control	All	Treated	Control	Weighted Control	All	Treated	Control	Weighted Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Complete questionnaire	-.053	-.082	-.038	-.072	.066	.126	.037	.019	.007	.022	.000	-.026
	(1.001)	(1.021)	(.991)	(1.029)	(.973)	(.954)	(.981)	(1.003)	(.989)	(.993)	(.986)	(1.017)
First quartile (P25)	.272	.285	.266	.28	.221	.195	.234	.24	.246	.24	.249	.26
Observations	5,430	1,843	3,587	3,587	5,581	1,841	3,740	3,740	11,011	3,684	7,327	7,327
Maths questionnaire	-.008	.001	-.013	.013	.002	.03	-.012	-.011	-.003	.016	-.013	.001
	(.984)	(.997)	(.978)	(.999)	(.972)	(.99)	(.963)	(.977)	(.978)	(.993)	(.97)	(.988)
First quartile (P25)	.244	.249	.241	.234	.244	.221	.255	.265	.244	.235	.249	.249
Observations	4,987	1,702	3,285	3,285	5,230	1,780	3,500	3,500	10,217	3,432	6,785	6,785
Reading questionnaire	.038	.043	.035	-.001	-.012	-.03	.001	.005	.013	.006	.018	.002
	(.991)	(.996)	(.987)	(1.003)	(.971)	(.992)	(.955)	(.947)	(.981)	(.995)	(.971)	(.975)
First quartile (P25)	.237	.236	.237	.249	.248	.259	.24	.238	.242	.248	.238	.243
Observations	3,983	1,692	2,287	2,287	4,118	1,713	2,405	2,405	8,101	3,409	4,692	4,692
Science questionnaire	-.028	-.004	-.047	-.061	.04	.047	.035	.054	.007	.022	-.005	-.004
	(.993)	(.997)	(.989)	(1.011)	(.973)	(.961)	(.981)	(.987)	(.983)	(.979)	(.986)	(1.001)
First quartile (P25)	.266	.266	.266	.288	.236	.244	.23	.219	.251	.255	.247	.254
Observations	4,102	1,765	2,337	2,337	4,309	1,778	2,531	2,531	8,441	3,543	4,868	4,868

Standard deviations in parentheses.

5 The empirical strategy

We study the effects of the PAE on the student's rate of decline in test performance and on her probability of falling behind the general progress of the group (having a rate decline in the first quartile of the rate decline distribution). To the extent that we cannot observe whether a particular student actually received the treatment, by selecting the student as the unit of observation, we are aware that we can only consider her *potentially* treated. Nevertheless, we address this point below and attempt to provide a cleaner estimate of the true effect of the PAE by decomposing our evaluation sample. In addition, we study the impact of the program while considering the school to be the treatment unit.

In the evaluation literature, data often come from non-randomized studies. The main assumption is that individuals' participation in the policy intervention can be considered a random event or, at least, independent of treated and control individuals' characteristics (see Myoung-JaeLee (2005)). However, selection into the treatment is not independent of treated and control individuals' characteristics. Propensity score matching is a method to reduce the bias in the estimation of treatment effects when using such datasets. The propensity score is defined by Rosenbaum and Rubin (1984) as the probability of being treated considering those variables included in the set of regressors. The method proposes to summarize the pre-treatment characteristics of each subject into a single-index variable (the propensity score) that makes the matching feasible. This index is built based on the estimation of the probability of being treated, $p(X_i)$, where X_i denote the vector of pre-treatment characteristics. If D_i denote a binary variable that indicates exposure to the treatment:

$$D_i = \begin{cases} 1 & \text{if treated} \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

the propensity score is defined as the probability of PAE participation conditional on some pre-treatment characteristics, X_i:

$$p(X_i) \equiv Pr(D_i = 1|X_i) = E(D|X_i) \tag{3}$$

Now, let Y_i^1 denote the potential outcome that student i would have obtained had she

better than girls) but not in the reading cluster (in which girls tend to outperform boys). Results available upon request.

received the PAE treatment and Y_i^0 had she not received the PAE treatment. We denote by Y_i the outcome (rate of decline or probability of falling into the first quartile of the rate decline distribution), where $Y_i = D_i Y_i^1 + (1 - D_i) Y_i^0$. Therefore, the average effect we are interested in estimating when evaluating the PAE is

$$\tau = E(Y_i^1 | D = 1, X_i) - E(Y_i^0 | D = 1, X_i) \tag{4}$$

The second term in the equation above is the counterfactual outcome in the absence of the treatment and thus is unobservable and must be estimated. This is achieved by using the outcomes of control students, that is, students in schools where the PAE was not implemented at all. It requires that the characteristics of the control and treatment group be as similar as possible. In our sample, as previously mentioned, treated and control students differ in their demographic characteristics, in socioeconomic background and attend different schools (see Table 2). To solve this problem, we use information on demographic, parental and school characteristics in the PISA 2012 database to *re-weight* the sample of controls such that they can provide a counterfactual to the PISA outcomes of the treated students. Formally, under the standard assumptions of conditional independence or unconfoundedness:

$$(Y_i^1, Y_i^0) \perp D_i \mid X_i \tag{5}$$

that is, within each cell defined by X_i, treatment is random, or similarly, the selection into treatment depends only on the observables X_i, and common support:

$$p(X_i) \in (0, 1), \tag{6}$$

we have that:

$$E(Y_i^0 | D = 1, X_i) \equiv E(\omega(x_i) Y_i | D = 0, X_i) \tag{7}$$

where $\omega(x_i) = \frac{1-\pi}{\pi} \times \frac{p(X_i)}{1-p(X_i)}$ and $\pi = \Pr(D_i = 1)$.

This expression indicates that we can identify the mean impact on treated individuals were they to have not received the treatment, $E(Y_i^0 | D = 1, X)$, by re-weighting the sample of controls. Observe that the weights, $\omega(x_i)$, increase the relevance in the control sample of those individuals who are very similar to treated students, where similarity is defined here by the predicted probability of participation in a logit that explains participation given pre-treatment characteristics, that is, by the propensity score, $p(X_i)$. We therefore compute the *inverse probability weighting estimator (IPWE)*. This estimator is achieved by regressing the outcome variable (either the rate of decline or the probability of falling behind the lowest quartile) on the treatment, where each observation is weighted by $\omega(x_i)$.[23] Since, through the consideration of the propensity score in the weighting procedure, there is a control for all covariates, X_i, in this estimation there is no need to include them. In any case, we may also include the covariates, X_i, as a robustness check. To the extend that we observe that boys and girls differ in rate of decline in performance, we also analyze whether they equally benefited from the program by adding an interaction term for the treatment and student's gender.

Finally, we comment on the validity of the two assumptions we make: unconfoundedness and common support. If the first assumption is not satisfied, this means that program participation could be due, among other reasons, to special interest by parents, teachers or school principals. If these variables are positively correlated with the distribution of potential outcomes (i.e., more interested parents or teachers are also more likely to yield better student non-cognitive skills), then our estimates of the impact of the PAE would be biased; in particular, they would be overestimating the true impact of the program. However, these unobserved school characteristics might also be negatively correlated with students' outcomes, for example, the existence of a difficult student body at the school. In that case, then our previous results would be underestimating the true impact of the program. This assumption is therefore crucial. We attempt to address it by including a set of variables that capture these parent, teacher and school characteristics (particularly, the school ESCS and whether teachers affect school climate).[24] The second assumption, the common support, can be tested by comparing the propensity score densities of the treated and control groups. We check this assumption graphically in Figure 3. As it can be observed, the common support assumption holds in our sample. Although the two distributions differ in form, the figure shows how similar the control and treatment samples are. The support of the values of the propensity score of treated students (solid line) and that of the control (dotted line) are the same: both ranges from 0 to approximately 0.8. In addition,

[23]See García-Pérez and Hidalgo-Hidalgo (2017) and Hospido et al. (2015) for a similar approach and Hirano et al. (2003) or Busso et al. (2014) for methodological details.

[24]García-Pérez and Hidalgo-Hidalgo (2017), using the PISA 2009 dataset to characterize possible selection bias, show that no selection bias exists. They find that, if any, possible differences can be explained by differences in individual, parental and school characteristics. Accounting for these differences completely attenuates the selection bias. Therefore, this suggests that it is feasible to obtain estimates of the impact of PAE participation on non-cognitive skills with no selection bias by re-weighting the sample according to student, family and school characteristics, as we do.

there is no concentration of predicted values around zero or one (which would mean that there are no comparable control students for some treated students).

5.1 Participation in the remedial program

We estimate the predicted probability of participation in the remedial education program (PAE) as a function of a set of characteristics of the students, parents and schools, i.e., the propensity score, $p(X_i)$. The set of variables included in X_i was chosen according to the differences in mean covariates in Table 2. We include the initial test score, measured as the average score in the first five questions of the first cluster, to control for student's cognitive abilities. Excluding such variable from the analysis does not change the results. We also control for gender, immigrant status, whether the student repeated a grade once or for more than one academic year, and whether the student attended pre-primary education. Regarding socioeconomic variables, we include the mother education level and the index of educational materials at home. Finally, we also add a set of school characteristics, including the student-teacher ratio, its mean socioeconomic index, its size, the proportion of dropouts, and an indicator of whether teachers favor good school climate. We then augment the basic logit model by including interactions that were statistically different from zero according to a two-sided t-test. This set of variables might affect the probability of participating in the program according to differences in mean covariates as commented above in Table 2. The final specification is shown in Table 4. The first column presents the estimates of the propensity score for the treatment. Its weights are used to estimate the impact of PAE on the general rate of decline of the complete questionnaire. Columns (2) to (4) present the estimates of the propensity score for the treatment whose weights are used to estimate the impact of the program on the rate of decline of maths, reading and science questions, respectively. As it can be observed, the specifications of the four propensity scores are the same.[25] This allows us to obtain comparable results across the different treatments.

[25]The only differences are that *migrant* for the reading questionnaire and *repeated more than once* for the science questionnaire do not satisfy the balancing property.

Figure 3: Propensity Score Support

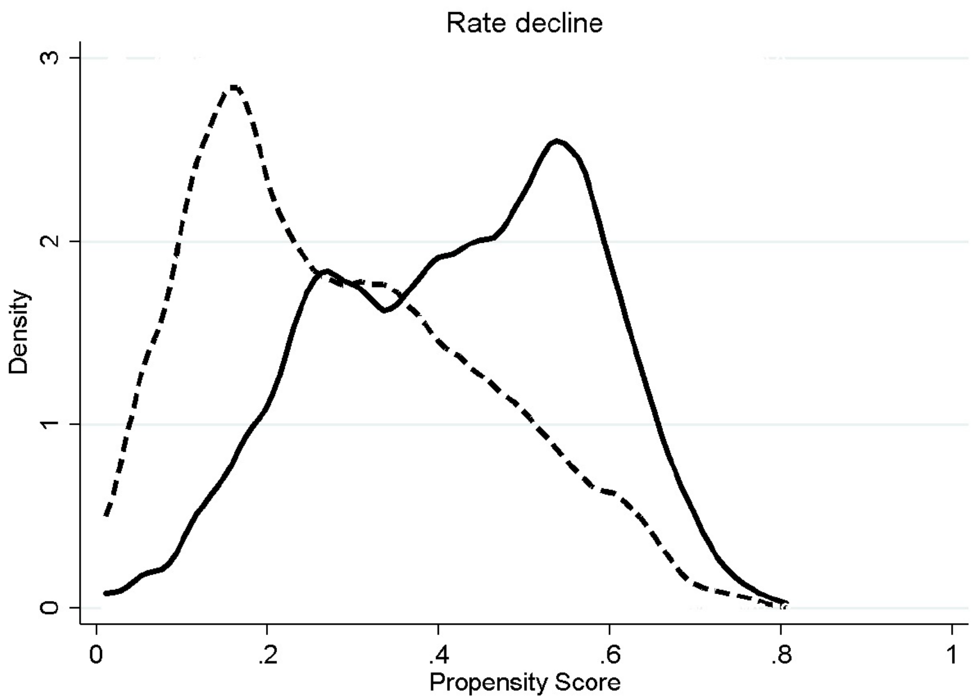


Table 4: Propensity score estimation - Probability of being treated

	(1)	(2)	(3)	(4)
		Rate decline		
	Complete	Maths	Reading	Science
Individual variables				
Initial test score[a]	0.078	-0.016	0.111	-0.053
	(0.094)	(0.103)	(0.139)	(0.103)
Girl(=1)	-0.037	-0.045	-0.014	-0.132***
	(0.039)	(0.039)	(0.048)	(0.049)
Migrant(=1)	0.455***	0.469***	-	0.481***
	(0.146)	(0.147)		(0.150)
Repeated once(=1)	0.148**	0.136**	0.218***	0.022
	(0.060)	(0.061)	(0.070)	(0.063)
Repeated more than once(=1)	0.190*	0.174*	0.225*	-
	(0.102)	(0.104)	(0.121)	
Attended kindergarden(=1)	-0.048	-0.044	-0.142	-0.045
	(0.098)	(0.098)	(0.106)	(0.102)
Socioeconomic variables				
Index of education	0.007	0.011	0.006	-0.036
possession[b]	(0.033)	(0.033)	(0.037)	(0.037)
Mother highly educated(=1)[c]	-0.043	-0.042	-0.049	-0.077
	(0.079)	(0.078)	(0.086)	(0.087)
School variables				
School size	0.004**	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Prob. dropouts	0.245	0.367	0.380	0.369
in high quartile(=1)	(0.328)	(0.268)	(0.268)	(0.267)
ESCS[d]	-0.974***	-0.975***	-1.054***	-1.030***
	(0.329)	(0.330)	(0.335)	(0.330)
Student-Teacher Ratio	-0.035	-0.036	-0.037	-0.034
	(0.024)	(0.027)	(0.028)	(0.023)
School climate-teacher(=1)[e]	0.615**	0.619**	0.604**	0.614**
	(0.251)	(0.252)	(0.254)	(0.252)
Observations	10,975	10,958	7,298	7,424

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We also include regions, interactions between regions and some individual characteristics and school size squared.

[a] Initial test score corresponds to the average score in the first five questions of the first cluster of the test.

[b] The index of education possession indicates whether the home possesses a desk and a quiet place to study, a computer and/or educational software and books to help with school work, and a dictionary. It ranges between -3.93 and 1.12.

[c] The mother is defined as highly educated if she has achieved at least tertiary education.

[d] Index of economic, social, and cultural status.

[e] It is a dummy equal to 1 if the school is below the median value of the index of teacher-related factors affecting school climate. Positive values indicate that the teacher-related behaviors hinder learning to a lesser extent. The index ranges between -3.2778 + 2.8533.

The estimates in the first column overall confirm the information provided in Table 2. The proportion of boys in a school does not seem to affect the likelihood that a school joins the program. On the contrary, schools with a high percentage of migrants or grade-repeaters are more likely to offer the program than other schools. The mean initial test score at the school level however does not affect the probability that the school offer the program. Observe that, once a complete set of control variables is considered, both parental education and the index of educational materials at home do not seem to influence the probability of being treated. Regarding school variables, those schools with poorer socioeconomic index, larger size, an a larger index of school climate have a higher chance of being treated. Finally, observe that the results of the propensity score when we consider the whole questionnaire are very similar to the ones obtained when we desegregate in the three specific questionnaires: maths, reading and science.

To conclude, column (5) of Table 2 presents the means of the control sample once the latter is re-weighted by $\omega(x_i) = \frac{1-\pi}{\pi} \times \frac{p(X_i)}{1-p(X_i)}$.[26] Column (6) reports the differences in characteristics between treated and re-weighted controls. These are not statistically different from one another, particularly for the set of controls considered in the propensity score estimation (i.e., the balancing property is satisfied). Finally, note that the sample is also similar along characteristics that we do not include in the propensity score (ESCS and father's education).[27] The similar composition of treated and re-weighted control groups even in characteristics omitted from the propensity score reinforces the credibility of the assumption that treated and re-weighted control students would have performed similarly had the treated students not been treated.[28]

6 The overall impact of the intervention on Rate decline

In this section, we comment on the overall impact of the program on students' test performance. The estimated general effect of the program on the ability to sustain test performance in the complete questionnaire is reported in Table 5. It presents the estimated impact of the treatment on mean rate of decline and on the probability of belonging to the first quartile in the rate of

[26]Therefore for those observations with missing values for some of the variables included in the propensity score, the estimated propensity score will be missing and, thus the weight variable will be missing too. This explains the difference between the controls observations in column (3) in Table 2 (7,441) and the weighted controls observations in column (5) in the same table (7,331).

[27]Exceptions are the proportion of migrants, parental pressure on teachers and principal enhancement of school reputation. The latter is lower in the treatment group while the others are lower in the control group.

[28]See Lavy and Schlosser (2005) or Hospido et al. (2015) for a similar test.

decline distribution. This is analyzed for the complete questionnaire (top panel), and the maths, reading and science specific questionnaires (rest of panels). Recall that we control for students' initial test score.[29] The rate of decline is standardized with the average and standard deviation of the sample of students in the complete, maths, reading and science questionnaires, respectively.

The first two columns, and as a benchmark, show the results of a simple OLS estimation without and with covariates. The estimated coefficient in the two cases is not significant. However, recall that this approach produces estimates without taking into account that treated and control students differ in characteristics other than the treatment which, in turn, also affect their probability of being treated. The third column shows the re-weighting estimate without covariates. This result can also be inferred from the first row in Table 3. As it can be observed there, the rate of decline among the treated is equal to 0.022, while that of the re-weighted control group is equal to -0.026. The 0.048 difference is the observed impact of the program. The standard error accounts for arbitrary correlation at the school level and is equal to 0.024; thus, the estimate is statistically significant at the 5% confidence level. The effect is very similar (0.041) when we include all of the variables considered in the logit model used to obtain the weights and it is statistically significant at the 10% confidence level. The robustness of this result suggests that the specification of the model that predicts PAE participation is appropriate. In addition, we go further and compare each treated student with her most similar associated control counterparts and thus provide results using several nearest neighbor propensity score estimators. In particular, we provide estimators by varying the number of nearest neighbors considered in the estimation from 2 to 8 (NNPS(2) to NNPS(8) in columns 5 to 8). As it can be observed, the results are quite similar to those obtained by using the inverse probability weighting estimator. In particular, the larger the number of nearest neighbors used, the more similar the results are to the IPWE ones. To summarize, we find that the program improved mean rate of decline by between 0.04 and 0.05 of one standard deviation.[30]

Results in rows (3) and (4) show the estimated impact of the treatment on the probability of belonging to the first quartile in the rate of decline distribution. Again the first two columns

[29] Excluding such variable from the analysis does not change the results (available upon request).

[30] We also used alternative definitions of correct answer and difficulty of the question. Main results in the paper are robust to these other definitions. See Section A in the Supplementary Material.

Table 5: The impact of PAE on Rate decline

	OLS		IPWE		NNPS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complete questionnaire								
Level								
PAE	0.021	0.034	0.048**	0.041*	0.031	0.050**	0.044*	0.040*
	(0.021)	(0.022)	(0.024)	(0.023)	(0.027)	(0.025)	(0.024)	(0.023)
P25 of the entire sample								
PAE	-0.010	-0.015	-0.020**	-0.019**	-0.010	-0.018	-0.017	-0.016
	(0.009)	(0.009)	(0.010)	(0.010)	(0.012)	(0.011)	(0.011)	(0.010)
Controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes
No. matches per obs.	-	-	-	-	2	4	6	8
Observations	11,089	10,964	11,011	10,964	10,964	10,964	10,964	10,964
Maths questionnaire								
Level								
PAE	0.024	0.013	0.013	0.014	-0.020	0.012	0.013	0.012
	(0.021)	(0.021)	(0.023)	(0.021)	(0.026)	(0.025)	(0.024)	(0.023)
P25 of the entire sample								
PAE	-0.011	-0.009	-0.011	-0.012	-0.003	-0.014	-0.014	-0.014
	(0.009)	(0.010)	(0.010)	(0.010)	(0.012)	(0.011)	(0.011)	(0.010)
Controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes
No. matches per obs.	-	-	-	-	2	4	6	8
Observations	10,570	10,437	10,487	10,437	10,437	10,437	10,437	10,437
Reading questionnaire								
Level								
PAE	-0.026	-0.001	0.004	0.005	-0.010	-0.005	-0.015	-0.013
	(0.029)	(0.025)	(0.030)	(0.025)	(0.032)	(0.029)	(0.028)	(0.028)
P25 of the entire sample								
PAE	0.016	0.005	0.004	0.002	0.008	0.010	0.013	0.012
	(0.012)	(0.011)	(0.013)	(0.011)	(0.014)	(0.013)	(0.013)	(0.012)
Controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes
No. matches per obs.	-	-	-	-	2	4	6	8
Observations	10,262	7,023	8,101	7,023	7,023	7,023	7,023	7,023
Science questionnaire								
Level								
PAE	0.024	0.029	0.026	0.036	0.025	0.014	0.012	0.012
	(0.026)	(0.023)	(0.026)	(0.023)	(0.030)	(0.028)	(0.027)	(0.027)
P25 of the entire sample								
PAE	0.004	0.004	0.001	0.000	0.003	0.006	0.008	0.011
	(0.012)	(0.010)	(0.012)	(0.010)	(0.014)	(0.013)	(0.012)	(0.012)
Controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes
No. matches per obs.	-	-	-	-	2	4	6	8
Observations	10,627	7,296	8,441	7,296	7,296	7,296	7,296	7,296

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

present the result from a simple OLS model without and with covariates. Columns (3) and (4) presents results using re-weighting estimates and columns (5) to (8) results using the nearest neighbor propensity score matching. The results are the same when re-weighting estimates are used without and with covariates and are consistent with previous findings. As before, the result in column (3) can also be inferred from Table 3. The program reduced the probability of belonging to the bottom quartile in the complete questionnaire distribution by 2 percentage points.[31]

The rest of panels show the impact of the program using the maths, reading and science specific questionnaires. The positive impact of the program on the rate of decline in the complete questionnaire is less precisely estimated when we analyze the subjects questionnaire separately. The coefficients mainly go in the same direction as for the complete questionnaire, although we do not observe statistically significant results. A plausible explanation could be the reduced number of observations in those analyses.

In addition to the student ability to sustain performance, we considered other measures of non-cognitive skills. On the one hand we considered another non-self assessed measure: the number of items reached in the test. We do not find statistically significant results on the average number of items reached, but again lower achievers show to benefit from the program: the PAE reduced the probability of belonging to the bottom part of the distribution of the number of item reached (see Section C in the Supplementary Material). On the other hand we analyzed the impact of the program on self-assessed measures of non-cognitive skills, namely absenteeism, truancy, discipline, self-confidence, sense of belonging to the school and perception of learning in class. Results are mostly not statistically significant, excepting for discipline. Students declare to behave better in class, especially if boys (see descriptive statistics and results in Section D in the Supplementary Material). Therefore, our findings are in line to results for similar interventions in the US as reviewed by Heckman (2000). Finally, we complement our analysis on non-cognitive skills by studying the impact of the program on initial performance and final score in the PISA test. Results can be found in Section E in the Supplementary Material. As can be observed, the program increases students' initial score on average (however it does not improve the initial score among those in the bottom part of the distribution). Therefore, as the program improves student's rate of decline on average and among those falling behind, it

[31] In addition we checked whether the order of the subjects, that is, whether maths is taken before reading and vice versa, could be relevant for differences in the rate of decline. Results show that it is not the case (see Section B in the Supplementary Material).

increases students' final score on average and among the poor performing ones, thus confirming previous results in the literature (García-Pérez and Hidalgo-Hidalgo (2017)).

6.1 Sub-sample analysis

As previously noted, the results for the full sample presented above might not precisely capture the true impact of the PAE. On the one hand, we are assuming that all of the students in schools with the PAE are treated, while some of them might not have received remedial education at all. By doing so, we are underestimating the impact of the PAE. On the other hand, by considering all of the students in the PAE school as treated, we might be capturing peer effects of treated on non-treated students. This assumption can lead to an overestimation of the impact of the PAE on treated students. In order to address these concerns we further explore the impact of the program. To argue that the effect analyzed is close to the actual effect of the intervention on treated students, we focus our main analysis on two sub-samples of our treated students group. In particular, we split that group according to some pre-treatment characteristics, namely the proportion of migrants at the school and the parental education level. These variables are appropriate as, even though they affect the probability of participating in the PAE, they are not included in the propensity score estimation as they do not satisfy the balancing property. This allows us to use the same specification for the propensity score as in the rest of the paper and get comparable results. In addition, we also replicate the same analysis as above but considering the school as the unit of analysis, instead of the student. Results are in line to those at the student level, see Section F in the Supplementary Material.

6.1.1 Disadvantaged students

First we consider treated students at schools where the proportion of migrants is above the median value of the distribution of this variable for all public schools. By considering students in these types of schools, we increase the likelihood that they actually participated in the program. Similarly, we consider treated students with non-educated parents.[32] The first four columns of Table 6 provides results for the impact of the program on the rate of decline and the

[32] In this analysis only treated students are split into two sub-samples. Alternatively, we could split both treated and controls into two sub-samples. Results of this alternative exercise, available upon request, are similar to the ones found here. This is because control students at schools with a proportion of migrants above the median might not be that similar to treated students and thus receive a low weight. A similar reasoning can be applied to the results found for the sub-sample of students with non-educated parents. Parents are defined as non-educated if their level of education is lower or equal to secondary school.

probability of falling into the bottom quartile of the rate of decline distribution. Rows (2) to (4) provide results for the sub-sample of students at schools with the proportion of migrants above the median. Rows (6) to (8) provide results for the sub-sample of students in non-educated families.

The estimated impact of the program on the rate of decline is an increase of 0.047 of one standard deviation, in the sub-sample of schools with migrants above the median, which is very close to the impact on the full sample of students (between 0.04 and 0.05). The probability of belonging to the bottom quartile is reduced by between 2.6 and 2.7 p.p overall, when considering schools with migrants above the median. Thus, again, by considering the full sample of students, we came close to estimating the true impact of the PAE on moving students out of low-skills status, which is the main objective of the program. The overall impact of the program is less precisely estimated when considering the sample of students with non-educated families, but confirms the previous results. The coefficients are in line with those obtained with the subsample of schools with migrants above the median and with the full sample, but standard errors are bigger.

6.1.2 Privileged students

Next we consider treated students at schools where the proportion of migrants is below the median value of the distribution. By considering students in these types of schools we reduce the likelihood that they actually participated in the program. Similarly, we consider treated students with educated parents. The last four columns of Table 6 provides results for the impact of the program on the rate of decline and the probability of falling into the bottom quartile of the rate decline distribution.

As can be observed, no impact of the program is found among students in schools with a low proportion of migrants.[33] However, among students with educated parents the impact on the rate of decline is slightly larger than among the whole sample (0.05-0.06 vs. 0.04-0.05 interval). There are two main explanations to this finding. On the one hand, if the number of true treated students in these schools was indeed high, then we are capturing the direct effect of the program which seems to be slightly larger among students with educated parents (that is, PAE and parental education are complements). On the other hand, if the number of true treated students in these schools was indeed low, then we are capturing spillover effects: students who participated have positively benefited the rest.

[33] Again this finding confirms previous results by García-Pérez and Hidalgo-Hidalgo (2017).

Table 6: The impact of PAE on Rate decline (Subgroups)

	OLS		IPWE		OLS		IPWE	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Schools with many migrants				**Schools with few migrants**			
	Complete questionnaire							
	Level							
PAE	0.013	0.040	0.047*	0.042	0.025	0.025	0.042	0.031
	(0.025)	(0.026)	(0.029)	(0.027)	(0.032)	(0.032)	(0.033)	(0.031)
	P25 of the entire sample							
PAE	-0.011	-0.021*	-0.027**	-0.026**	-0.003	-0.005	-0.007	-0.007
	(0.010)	(0.011)	(0.012)	(0.011)	(0.013)	(0.014)	(0.014)	(0.013)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,835	9,722	9,757	9,722	8,757	8,665	8,679	8,665
	Non-educated families				**Educated families**			
	Level							
PAE	0.002	0.010	0.023	0.014	0.043	0.048	0.060*	0.053*
	(0.027)	(0.026)	(0.030)	(0.028)	(0.029)	(0.030)	(0.033)	(0.030)
	P25 of the entire sample							
PAE	-0.006	-0.012	-0.016	-0.015	-0.012	-0.014	-0.015	-0.015
	(0.011)	(0.011)	(0.012)	(0.011)	(0.013)	(0.013)	(0.015)	(0.013)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,513	9,394	9,435	9,394	9,056	8,952	8,978	8,952

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.2 On the quality of the program offered by each school

We use information on the number of students, professors and monitors who actually participated to the PAE to measure the school degree of commitment with the program, and thus the quality of the remedial education activity offered there. The same schools involved in the program provided such information and even though we do not know who are the students actually treated we can get a sense of the extent of the implementation of the policy. In particular, for each treated school we compute the PAE student-teacher ratio as the number of students involved in the remedial program per professor and/or monitor. Table 7 reports its average value for the year of the PISA test.[34] It also shows that, on average, in each treated school there are 30 students who receive remedial education support, with a relative high standard deviation. This amount corresponds to 6% of the students in those schools. As commented in Section 4 above, both teachers from the own school and monitors provided support to the students in the program. As can be observed in Table 7 there are more professors than monitors performing the remedial activities (roughly 3 and 2, respectively) and they count for the 4% of all professors in that school. It implies that during remedial education classes there are on average 9 students per teacher, our PAE student-teacher ratio.

One limitation of such analysis is that we do not have information for the whole sample of treated schools: only 65% of them provided data on the implementation of the program. Consolingly, students in schools sharing the information are comparable to students in schools not sharing them for most of the characteristics we use in the analysis, as shown in Table 1 of Section G in Supplementary Material.[35]

Table 8 provides results for the impact of the PAE on the rate of decline and the probability of falling into the bottom quartile of the rate of decline distribution depending on the school student-teacher ratio in remedial classes. First, we compare students in schools whose PAE

[34] The number of schools for which we have the full set of information is 84, as reported in Table 1 of Section G in the Supplementary Material. Each school may provide only some information, i.e. some schools can report the number of students but not the number of professors or viceversa. For this reason, in Table 7 we observe a different number of observations for each variable.

[35] In schools providing information on the implementation of the PAE there are slightly more female students who did not attend kindergarden and who belongs to the upper quartile of the ESCS distribution.

Table 7: Quality of PAE schools: some summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
# students	95	30.651	14.449	8.5	99.25
% students	89	.066	.054	.011	.45
# professors	104	2.705	3.419	0	14
# monitors	104	1.6	1.87	0	8
% professors and/or monitors	101	.041	.049	0	.256
student-teacher ratio	95	9.384	7.5812	2.353	45

It reports the summary statistics for the year of the PISA test for the treated schools which provided the data.

Table 8: The impact of PAE on Rate decline (PAE Student-Teacher ratio)

	OLS		IPWE	
	(1)	(2)	(3)	(4)
PAE Student-Teacher ratio lower than the median				
	Complete questionnaire			
	Level			
PAE	0.037	0.067*	0.072*	0.067*
	(0.035)	(0.037)	(0.039)	(0.037)
	P25 of the entire sample			
PAE	-0.032**	-0.042***	-0.044***	-0.043***
	(0.013)	(0.013)	(0.014)	(0.013)
Controls	No	Yes	No	Yes
Observations	8,731	8,638	8,653	8,638
PAE Student-Teacher ratio higher than the median				
	Level			
PAE	0.043*	0.043	0.051*	0.044
	(0.026)	(0.027)	(0.026)	(0.027)
	P25 of the entire sample			
PAE	-0.008	-0.009	-0.012	-0.012
	(0.013)	(0.013)	(0.013)	(0.013)
Controls	No	Yes	No	Yes
Observations	8,774	8,675	8,696	8,675
Test of equality of the coefficients				
Level	no	no	no	no
P25 of the entire sample	no	reject	reject	reject

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

student-teacher ratio is higher than its sample median to students in control schools (top panel). Second, we compare students in schools whose PAE student-teacher ratio is lower than its sample median to students in control schools (bottom panel). A low PAE student-teacher ratio should be favorable as it suggests a better quality in the implementation of the program. It is also informative of the intensity of the remedial education activity.

In schools with a low PAE student-teacher ratio, the estimated impact of the program on the rate of decline is an increase of roughly 0.07 of one standard deviation, which is 21% higher than the impact on the full sample of schools (between 0.04 and 0.05). The probability of belonging to the bottom quartile is reduced by 4.3 p.p., so double the effect of the full sample of schools. The overall impact of the program is less precisely estimated when considering the sample of students in PAE with a student-teacher ratio higher than its median. When comparing performance in both type of schools, in particular on the level of rate of decline, we find that the impact of the program in low and high student-teacher ratio schools are not statistically significant different, suggesting that on average the effect is comparable for the two types of schools (test of equality of the coefficients). However, the benefits on the ability to sustain the test performance are much higher for underperforming students (less than P25 of the entire sample) who are in schools with a low PAE student-teacher ratio. Therefore, students in schools where the program was better implemented reassuringly benefit more from it, especially if they belong to the lower quartile of the distribution.

7 On the impact of the program by gender

The results in the descriptive statistics (Table 3 and Figure 2) show that boys and girls differ in their ability to sustain test performance. In particular, girls tend to outperform boys in terms of rate of decline in performance. Therefore, we analyze the impact of the program by student's gender. Results can be found in Table 9. Columns (1) to (4) show the estimated impact of the program on boys and columns (5) to (8) on girls.

Table 9: The impact of PAE on Rate decline by gender

	Boys				Girls			
	OLS		IPWE		OLS		IPWE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complete questionnaire								
Level								
PAE	-0.046	-0.021	-0.011	-0.012	0.089***	0.090***	0.106***	0.094***
	(0.029)	(0.029)	(0.032)	(0.031)	(0.027)	(0.027)	(0.031)	(0.030)
P25 of the entire sample								
PAE	0.018	0.011	0.005	0.005	-0.039***	-0.041***	-0.045***	-0.044***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.011)	(0.012)	(0.013)	(0.013)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,089	10,964	11,011	10,964	11,089	10,964	11,011	10,964
Maths questionnaire								
Level								
PAE	0.009	0.017	-0.010	0.010	0.038	0.009	0.037	0.018
	(0.029)	(0.028)	(0.032)	(0.029)	(0.029)	(0.026)	(0.032)	(0.028)
P25 of the entire sample								
PAE	0.010	0.008	0.019	0.013	-0.032**	-0.026**	-0.041***	-0.038***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)	(0.014)	(0.013)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	10,570	10,437	10,487	10,437	10,570	10,437	10,487	10,437
Reading questionnaire								
Level								
PAE	0.000	0.017	0.044	0.037	-0.052	-0.018	-0.035	-0.026
	(0.038)	(0.035)	(0.040)	(0.037)	(0.036)	(0.034)	(0.035)	(0.034)
P25 of the entire sample								
PAE	0.003	-0.003	-0.013	-0.011	0.028*	0.013	0.021	0.014
	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	10,262	7,023	8,101	7,023	10,262	7,023	8,101	7,023
Science questionnaire								
Level								
PAE	0.036	0.029	0.058	0.044	0.015	0.030	-0.007	0.028
	(0.033)	(0.032)	(0.036)	(0.034)	(0.031)	(0.029)	(0.032)	(0.029)
P25 of the entire sample								
PAE	0.000	0.008	-0.022	-0.009	0.007	0.000	0.024	0.010
	(0.015)	(0.014)	(0.016)	(0.014)	(0.014)	(0.014)	(0.016)	(0.015)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	10,627	7,296	8,441	7,296	10,627	7,296	8,441	7,296

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The rate of decline increases by about 0.10 of one standard deviation, only for girls. We find no effect among boys. That is, girls that participated in the program experience a lower decline in performance than their similar counterparts who did not participated in it. The program participation also reduced the probability of belonging to the bottom quartile only among girls. As before, the result in column (7) can also be inferred from Table 3. The proportion of treated girls in the first quartile in the rate of decline distribution is equal to 0.195, while that of the re-weighted control group is equal to 0.24. The -0.044 difference is the observed impact of the program. That is, the program participation reduced the probability of belonging to the bottom quartile by 4.4 p.p. among girls. When focusing on maths, reading and science specific questionnaires we find that the program reduced the probability of belonging to the bottom quartile in the maths questionnaire by between 3.8 and 4.1 p.p. again only among girls. No robust effects are observed for the reading and science questionnaires. Therefore, we can conclude that the observed reduced probability of belonging to the bottom quartile in the rate of decline distribution for the complete questionnaire might be mostly driven by the impact on the maths specific questionnaires.[36]

We next replicate the analysis presented above by focusing on the impact on the program on boys and girls within the different subgroups: disadvantaged (at schools with a high proportion of migrants or with non-educated parents) and privileged (at schools with a low proportion of migrants or with educated parents).

Observe from Table 10 that the probability of falling behind into the bottom part of the distribution is reduced by 5 p.p. for those girls in the sub-sample of schools with migrants above the median and by 4 p.p. for those girls in the sub-sample of students in non-educated families. Therefore, the impact among girls in this subgroup is quite close to the impact among girls in the overall sample. Regarding the privileged group, it can be observed that the program had a impact only among girls. In addition, the impact on the rate of decline among girls with educated parents seems larger than among girls in the whole sample. A possible explanation could be that girls benefit more than boys from the complementarity between parental education and

[36]Similar to our previous analysis on the overall effect of the program, we checked whether the order of the subjects, that is, whether maths is taken before reading and vice versa, could be relevant for differences in the rate of decline between boys and girls. Results show that it is not the case (see Section B in the Supplementary Material).

Table 10: The impact of PAE on Rate decline by gender (Subgroups)

	Boys				Girls				Boys				Girls			
	OLS		IPWE		OLS		IPWE		OLS		IPWE		OLS		IPWE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Schools with many migrants								**Schools with few migrants**							
	Complete questionnaire															
	Level															
PAE	-0.054	-0.019	-0.008	-0.012	0.082**	0.099***	0.103***	0.097***	-0.032	-0.018	-0.005	0.000	0.085**	0.067*	0.090**	0.061
(0.034)	(0.033)	(0.038)	(0.036)	(0.032)	(0.033)	(0.037)	(0.035)	(0.043)	(0.043)	(0.045)	(0.044)	(0.039)	(0.038)	(0.041)	(0.039)	
	P25 of the entire sample															
PAE	0.018	0.007	-0.003	0.000	-0.041***	-0.049***	-0.051***	-0.052***	0.019	0.014	0.010	0.005	-0.027*	-0.024	-0.025	-0.019
	(0.015)	(0.015)	(0.016)	(0.016)	(0.013)	(0.013)	(0.016)	(0.015)	(0.021)	(0.021)	(0.022)	(0.021)	(0.016)	(0.017)	(0.017)	(0.017)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,835	9,722	9,757	9,722	9,835	9,722	9,757	9,722	8,757	8,665	8,679	8,665	8,757	8,665	8,679	8,665
	Non-educated families								**Educated families**							
	Level															
PAE	-0.058	-0.042	-0.022	-0.032	0.060*	0.059*	0.067*	0.05	-0.036	-0.016	-0.029	-0.023	0.132***	0.115***	0.156***	0.134***9
	(0.037)	(0.036)	(0.041)	(0.039)	(0.035)	(0.032)	(0.040)	(0.036	(0.040)	(0.039)	(0.044)	(0.041)	(0.036)	(0.035)	(0.041)	(0.038))
	P25 of the entire sample															
PAE	0.023	0.017	0.007	0.010	-0.034**	-0.039***	-0.038**	-0.040***	0.017	0.012	0.018	0.017	-0.045***	-0.042***	-0.052***	-0.049***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.013)	(0.014)	(0.016)	(0.015)	(0.018)	(0.018)	(0.020)	(0.019)	(0.015)	(0.016)	(0.018)	(0.017)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,513	9,394	9,435	9,394	9,513	9,394	9,435	9,394	9,056	8,952	8,978	8,952	9,056	8,952	8,978	8,952

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the remedial program. Alternatively, girls could also benefit more from spillovers.

Finally, the quality of the program offered at the school might have a differential effects for boys and girls. Table 11 summarizes the main findings.

Both the rate of decline and the probability of falling behind into the bottom part of the distribution equally reduce for girls in both types of schools, but the probability of falling behind into the bottom part of the distribution reduces for boys only in schools with a low PAE student-teacher ratio and this is statistically significantly different between schools with a low and schools with a high PAE student-teacher ratio.

7.1 Discussion

In this section we investigate the potential mechanisms explaining the impact of the program mostly on girls. First, girls could be over-represented in those percentiles in the test performance distribution where the impact of the PAE is larger. In order to check that, we estimate the impact of the PAE along certain percentiles of the rate of decline and the proportion of girls in these same percentiles. To compute the former we calculate the values of two Cumulative Distribution Function (CDF) of the rate decline for certain percentiles: the CDF of rate decline among treated students and the CDF of rate decline among re-weighted controls. Next, we present the difference between these two CDF (in particular the absolute value of the rate equal to the CDF treated/CDF weighted controls minus one). Figure 4 shows the results.

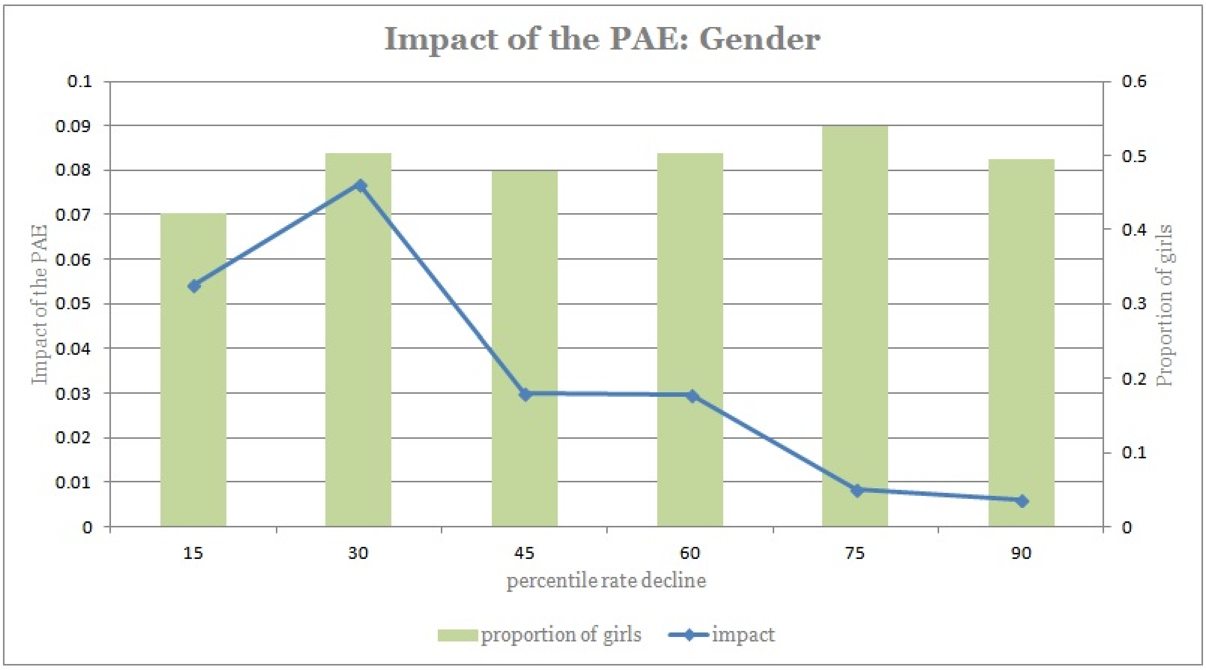
The x-axis reports the percentile in the rate decline, while on the y-axes we have both the proportion of girls (histograms) and the impact of the PAE (plot). We observe that the group of students who are more affected is in the lowest tail of the distribution, precisely they are the students whose rate of decline is lower than the 30 percentile in the distribution. Among these, and also along the entire distribution, girls and boys are evenly distributed. Therefore, the impact of the program only on girls is clearly not due to a larger proportion of girls in the percentiles where its impact is larger.

Table 11: The impact of PAE on Rate decline by gender (PAE Student-Teacher ratio)

	Boys				Girls			
	OLS		IPWE		OLS		IPWE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PAE Student-Teacher ratio lower than the median								
	Complete questionnaire							
	Level							
PAE	-0.018	0.007	0.031	0.019	0.089**	0.124***	0.109**	0.112**
	(0.050)	(0.048)	(0.053)	(0.048)	(0.040)	(0.041)	(0.046)	(0.044)
	P25 of the entire sample							
PAE	-0.019	-0.026	-0.039*	-0.036*	-0.044***	-0.056***	-0.047**	-0.050***
	(0.021)	(0.020)	(0.022)	(0.020)	(0.016)	(0.018)	(0.019)	(0.019)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	8,731	8,638	8,653	8,638	8,731	8,638	8,653	8,638
PAE Student-Teacher ratio higher than the median								
	Level							
PAE	-0.055	-0.033	-0.038	-0.029	0.143***	0.118***	0.141***	0.117***
	(0.037)	(0.038)	(0.039)	(0.037)	(0.036)	(0.037)	(0.036)	(0.038)
	P25 of the entire sample							
PAE	0.036*	0.029	0.027	0.024	-0.053***	-0.047***	-0.052***	-0.048***
	(0.018)	(0.019)	(0.019)	(0.019)	(0.015)	(0.016)	(0.016)	(0.016)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	8,774	8,675	8,696	8,675	8,774	8,675	8,696	8,675
Test of equality of the coefficients								
Level	no	no	no	no	no	no	no	no
P25 of the entire sample	no	reject	reject	reject	no	no	no	no

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4: Impact of the PAE: Gender



Second, girls could participate to the remedial program more than boys. The lack of data on individual participation to the program does not allow us to unquestionably exclude this possibility. However, based on observables, this concern is unlikely to apply. The students' characteristics by gender in treated schools are reported in Table 12.

Girls are less likely than boys to show characteristics associated to students targeted by a remedial education intervention. They are less likely to have repeated one or more grades and report a higher index of education possession. If we were expecting a differential participation to the program by gender, boys could participate more than girls to it.

Third, participation to the program could have lead to gender differences in test taking strategies, where test taking strategies are defined as any strategy that lead students to answer the questions in a different order than the one proposed. However, by using data also from PISA 2015 (whose test were given on the computer and navigation across question units was restricted), Balart and Oosterveen (2018) disregard the possibility that test taking strategies are a determinant for the gender differences in performance during the test. Therefore, a plausible explanation could be that girls participate more intensively and they better respond to the PAE suggesting that the remedial education program is more effective in improving skills other than cognitive for girls.

8 Concluding remarks

There is ample evidence of increasing inequality and poverty figures in developed countries.[37] This recent evidence pointing towards a worsening of the education level of the workforce have called the attention of policy makers and impelled them to improve it. In fact, one of the EU's education targets for 2020 is to reduce the rates of young people leaving early the education and training systems. National governments are currently being encouraged to undertake evidence-based education policies to reduce the adverse effects of the aforementioned facts. In addition, evidence in the US has shown that skills other than cognitive are more

[37] Recent evidence (OECD, 2013) suggests increases in inequality and poverty. This might be caused by the global crisis and might also reflect the fact that as a result of rapid technological change both low-skilled workers and low-achieving students are being left behind (see Freeman (2008) or Kanbur (2014)). Indeed, poor-achieving students are more likely to be early school leavers, which has long-run negative effects, increasing the risk of social exclusion and poverty. Their disadvantage on the labor market is reflected in high unemployment rates, below average wages and possibly high concentration in the informal employment. They are poorer than the average population and more likely to fall into poverty and remain poor, with consequences in increased inequality.

Table 12: Summary Statistics

Variable	(1) Girls	(2) Boys	(3) P-value Diff. (1)-(2)	(4) P-score Controls
Individual variables				
Initial test score[a]	.588	.625	.000	yes
	(.276)	(.27)		
Migrant(=1)	.152	.146	.606	yes
	(.36)	(.354)		
Repeated once(=1)	.241	.301	.000	yes
	(.428)	(.459)		
Repeated more than once(=1)	.084	.128	.000	yes
	(.278)	(.334)		
Attended kindergarden(=1)	.844	.815	.019	yes
	(.363)	(.388)		
Socioeconomic variables				
Index of education possession[b]	.097	-.014	.000	yes
	(.863)	(.907)		
Mother highly educated(=1)[c]	.3	.307	.653	yes
	(.458)	(.461)		
Father highly educated(=1)[d]	.278	.319	.007	no
	(.448)	(.466)		
School variables				
School size	622.138	621.489	.943	yes
	(274.93)	(281.311)		
Prop. of dropout	.114	.115	.832	yes
	(.110)	(.112)		
Prob. of dropout in	.32	.296	.121	yes
high quartile(=1)	(.466)	(.457)		
Prop. of migrants (school)	.15	.149	.912	no
	(.143)	(.144)		
ESCS[e]	-.375	-.366	.784	no
	(.976)	(.967)		
ESCS in high quartile(=1)	.152	.16	.504	yes
	(.36)	(.367)		
Student-Teacher Ratio	9.259	9.268	.884	yes
	(2.019)	(2.085)		
Principal enhance school's	.226	.22	.670	no
reputation(=1)[f]	(.418)	(.414)		
Parental pressure on teachers(=1)[g]	.401	.382	.236	no
	(.49)	(.486)		
School climate-teacher(=1)[h]	.696	.677	.221	yes
	(.46)	(.468)		
Rural(=1)[i]	.416	.406	.563	no
	(.493)	(.491)		
Observations	1,843	1,851		

Standard deviations in parentheses.

[a] Initial test score corresponds to the average score in the first five questions of the first cluster of the test.

[b] The index of education possession indicates whether the home possesses a desk and a quiet place to study, a computer and/or educational software and books to help with school work, and a dictionary. It ranges between -3.93 and 1.12.

[c] The mother is defined as highly educated if she has achieved at least tertiary education.

[d] The father is defined as highly educated if he has achieved at least tertiary education.

[e] Index of economic, social, and cultural status.

[f] The dummy is equal to 1 if the principal enhances school's reputation on weekly basis.

[g] The dummy is equal to 1 if the principal claims that parents exert pressure into teachers and principal to improve the school quality.

[h] It is a dummy equal to 1 if the school is below the median value of the index of teacher-related factors affecting school climate. Positive values indicate that the teacher-related behaviors hinder learning to a lesser extent. The index ranges between -3.2778 + 2.8533.

[i] It is a dummy equal to 1 if the school is located in a village or a small town.

likely affected by policy interventions at later stages of one persons' life, as remedial education programs are. Surprisingly, it is difficult to find empirical evidence regarding the effectiveness of most of these interventions especially in Europe and for remedial education programs. In this paper, we provide additional evidence by taking advantage of a remedial program aimed at teenagers and recently implemented in Spain (the Program for School Guidance (PAE). It offered additional instruction time for underperforming students from poor socioeconomic backgrounds.

Our main finding is that this program had a substantial positive effect on students' ability to sustain test performance. In particular, it helps girls in improving their rate of decline in performance during the PISA test. It reduced the probability of falling behind into the bottom of the rate of decline distribution by 4.4 p.p. and reduces the decline in performance during the test by almost 0.10 of one standard deviation. We found no impact of the program among boys. Such results suggest that remedial education programs might be particularly effective in improving non-cognitive skills if the treated students are girls. Therefore, since it is known that improvements in non-cognitive skills have similar effects to cognitive ones for a variety of long-term outcomes (such as job market or high education investments), the program proved to have a substantially positive impact on the treated youths life outcomes. This project contributes to the relatively scarce literature on the evaluation of remedial education programs for teenage students on pupils' non-cognitive skills in developed countries. By aiming at improving our understanding of the overall effectiveness of remedial education programs, our study might be highly relevant from a policy perspective. It provides a more comprehensive analysis of the strength of such programs.

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Supplementary Material to:

Test performance and Remedial Education: Good News for girls

Marianna Battaglia and Marisa Hidalgo-Hidalgo

A: Alternative definitions of correct answer and difficulty

Table 1: The impact of PAE on Rate decline - Partially corrected answers

	Boys				Girls				Overall			
	OLS		IPWE		OLS		IPWE		OLS		IPWE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
All sample												
	Level											
PAE	-0.043	-0.020	-0.014	-0.014	0.086***	0.085***	0.106**	0.092**	0.021	0.032	0.046*	0.039
	(0.030)	(0.030)	(0.032)	(0.031)	(0.028)	(0.028)	(0.033)	(0.031)	(0.022)	(0.022)	(0.024)	(0.024)
	P25 of the entire sample											
PAE	0.007	0.011	0.005	0.005	-0.046***	-0.048***	-0.053***	-0.051***	-0.014	-0.019*	-0.024**	-0.023**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.012)	(0.012)	(0.013)	(0.013)	(0.009)	(0.010)	(0.010)	(0.010)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,088	10,963	11,010	10,963	11,088	10,963	11,010	10,963	11,088	10,963	11,010	10,963
Schools with many immigrants and repeaters												
	Level											
PAE	-0.038	-0.009	-0.003	-0.002	0.073**	0.081***	0.080**	0.074**	0.017	0.036	0.039	0.036
	(0.031)	(0.030)	(0.034)	(0.032)	(0.030)	(0.030)	(0.036)	(0.034)	(0.022)	(0.023)	(0.025)	(0.024)
	P25 of the entire sample											
PAE	0.016	0.007	0.001	0.000	-0.042***	-0.048***	-0.045***	-0.046***	-0.013	-0.021**	-0.022**	-0.023**
	(0.014)	(0.014)	(0.015)	(0.015)	(0.013)	(0.013)	(0.014)	(0.014)	(0.009)	(0.010)	(0.010)	(0.010)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	10,437	10,319	10,359	10,319	10,437	10,319	10,359	10,319	10,437	10,319	10,359	10,319
Non-educated families												
	Level											
PAE	-0.055	-0.038	-0.007	-0.014	0.060*	0.057*	0.069	0.059	0.004	0.010	0.032	0.024
	(0.037)	(0.036)	(0.043)	(0.042)	(0.035)	(0.032)	(0.044)	(0.040)	(0.027)	(0.026)	(0.031)	(0.030)
	P25 of the entire sample											
PAE	0.021	0.013	0.003	0.004	-0.039***	-0.046***	-0.047***	-0.049***	-0.010	-0.017	-0.023*	-0.023*
	(0.017)	(0.017)	(0.018)	(0.018)	(0.014)	(0.013)	(0.016)	(0.016)	(0.011)	(0.011)	(0.012)	(0.012)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,512	9,393	6,744	6,703	9,512	9,393	6,744	6,703	9,512	9,393	6,744	6,703

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: The impact of PAE on Rate decline - Different measures of difficulty

	Boys				Girls				Overall			
	OLS		IPWE		OLS		IPWE		OLS		IPWE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
All sample - Difficulty equal to 1 if the answer is an open question												
					Level							
PAE	-0.043	-0.023	-0.018	-0.019	0.071**	0.068**	0.082***	0.069**	0.013	0.022	0.032	0.025
	(0.030)	(0.029)	(0.032)	(0.031)	(0.028)	(0.027)	(0.031)	(0.029)	(0.022)	(0.022)	(0.023)	(0.023)
					P25 of the entire sample							
PAE	0.025*	0.019	0.013	0.012	-0.03***	-0.03***	-0.034***	-0.032***	-0.002	-0.006	-0.011	-0.01
	(0.014)	(0.014)	(0.015)	(0.014)	(0.011)	(0.012)	(0.013)	(0.013)	(0.009)	(0.010)	(0.010)	(0.010)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,075	10,955	11,002	10,955	11,075	10,955	11,002	10,955	11,075	10,955	11,002	10,955
All sample - Difficulty as percentage of students who correctly answer to the question												
					Level							
PAE	-0.056*	-0.034	-0.019	-0.023	0.086***	0.095***	0.109***	0.101***	0.015	0.031	0.045*	0.039*
	(0.031)	(0.031)	(0.034)	(0.033)	(0.027)	(0.027)	(0.030)	(0.029)	(0.022)	(0.023)	(0.024)	(0.023)
					P25 of the entire sample							
PAE	0.026*	0.017	0.007	0.009	-0.041***	-0.047***	-0.05***	-0.050***	-0.007	-0.015	-0.022**	-0.02**
	(0.014)	(0.014)	(0.015)	(0.015)	(0.011)	(0.012)	(0.013)	(0.013)	(0.009)	(0.009)	(0.010)	(0.010)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,091	10,963	11,012	10,963	11,091	10,963	11,012	10,963	11,091	10,963	11,012	10,963

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B: Reading or Maths first

Table 1: The impact of PAE on Rate decline - Clusters order

	Boys		Girls		Overall		
	OLS	IPWE	OLS	IPWE	OLS	IPWE	
	(1)	(2)	(3)	(4)	(5)	(6)	Observations
All sample - Complete questionnaire							
				Level			
Reading after Maths	-0.015	-0.009	0.108**	0.100**	0.048	0.046	4,238
	(0.047)	(0.050)	(0.044)	(0.048)	(0.032)	(0.031)	
Maths after Reading	-0.031	-0.02	0.078**	0.086**	0.023	0.032	6,741
	(0.034)	(0.038)	(0.032)	(0.037)	(0.025)	(0.024)	
Chi2 test (p-value)	0.2149	0.0075	0.4179	0.0873			
				P25 of the entire sample			
Reading after Maths	0.021	0.021	-0.036*	-0.036*	-0.008	-0.008	4,238
	(0.021)	(0.021)	(0.020)	(0.020)	(0.015)	(0.014)	
Maths after Reading	0.006	0.006	-0.049***	-0.047***	-0.019*	-0.025**	6,741
	(0.015)	(0.015)	(0.015)	(0.015)	(0.011)	(0.011)	
Chi2 test (p-value)	0.5688	0.0092	0.9996	0.8422			

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As reported in Table 1 the order of the subject does not show to be relevant for the rate of decline in the complete questionnaire. We do observe that, independently of the order of clusters, the remedial program benefits slightly more girls than boys and that by gender taking reading after maths or viceversa is not statistically relevant (p-value of Chi2 test for equality in coefficients).

C: Item reached

Table 1: Students' outcomes: Item reached

	Boys				Girls				Overall			
	All	Treated	Control	Weighted Control	All	Treated	Control	Weighted Control	All	Treated	Control	Weighted Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Complete questionnaire	.973	.971	.973	.967	.974	.97	.976	.971	.973	.97	.975	.969
	(.072)	(.079)	(.068)	(.077)	(.063)	(.073)	(.057)	(.064)	(.068)	(.076)	(.063)	(.071)
First quartile (P25)	.285	.290	.283	.319	.297	.307	.293	.328	.292	.299	.288	.324
Observations	5,430	1,843	3,587	3,587	5,581	1,841	3,740	3,740	11,011	3,684	7,327	7,327

Standard deviations in parentheses.

Table 2: The impact of PAE on Item reached

	Boys				Girls				Overall			
	OLS		IPWE		OLS		IPWE		OLS		IPWE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
All sample												
	Level											
PAE	-0.000	0.004	0.004	0.005*	-0.004*	-0.000	-0.001	0.000	-0.003	0.002	0.001	0.003
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
	P25 of the entire sample											
PAE	0.005	-0.021	-0.029	-0.025	0.013	-0.015	-0.021	-0.022	0.009	-0.018	-0.025*	-0.024*
	(0.016)	(0.015)	(0.018)	(0.016)	(0.016)	(0.015)	(0.018)	(0.016)	(0.013)	(0.012)	(0.015)	(0.013)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,089	10,964	11,011	10,964	11,089	10,964	11,011	10,964	11,089	10,964	11,011	10,964

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A provides the summary statistics for the average number of items reached and Table B the impact of the PAE on this outcome. As can be observed, the program has no impact on the number of items reached overall, although it has a slightly statistically significant positive impact for boys. In addition, it reduced the probability of belonging to the bottom quartile in the distribution of item reached by 2.4 p.p. The results are consistent to choosing the minimum or the maximum last question answered. They are not reported but are available upon request.

D: Self-assessed measures

We examine here the impact of the program on students' self-assessed measures. In particular we consider, absenteeism and truancy, defined as whether the student does not show up at school or is usually late for it. This information is relevant since it is likely correlated with motivation and it may also predict worse test scores. The more one misses classes, the less likely can be motivated to learn or find it more difficult. Discipline is measured by the way students behave in class (disciplinary climate). Self-confidence is measured by self-reported ability to succeed with enough effort and confidence to perform well if wanted. Another way to measure self-confidence is sense of belonging to the group, in our case the school. We finally look at motivation towards schools: whether students think that school does prepare for life or it is considered a waste of time, and if it helps to get a job and improve career chances. Summary statistics for these variables can be found in Table 1 below.

Overall, we observe that discipline improves, especially for boys, but most of these measures do not change due to the program (Table 2).

Table 1: Students' outcomes: non-cognitive skills. Non cognitive self-assessed.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Boys				Girls				Overall			
	All	Treated	Control	Weighted Control	All	Treated	Control	Weighted Control	All	Treated	Control	Weighted Control
Motivation												
Absenteism(=1)	.239	.249	.233	.272	.241	.253	.235	.281	.24	.251	.234	.277
	(.426)	(.433)	(.423)	(.445)	(.428)	(.435)	(.424)	(.45)	(.427)	(.434)	(.424)	(.447)
Observations	5,412	1,832	3,610	3,578	5,583	1,832	3,751	3,737	11,025	3,664	7,361	7,315
Truancy(=1)	.367	.385	.359	.376	.364	.382	.356	.379	.366	.383	.357	.377
	(.482)	(.487)	(.48)	(.484)	(.481)	(.486)	(.479)	(.485)	(.482)	(.486)	(.479)	(.485)
Observations	5,410	1,823	3,587	3,555	5,553	1,818	3,735	3,721	10,963	3,641	7,322	7,276
Discipline												
Bad climate(=1)	.389	.372	.397	.408	.356	.343	.362	.363	.372	.358	.379	.386
	(.487)	(.484)	(.489)	(.492)	(.479)	(.475)	(.481)	(.481)	(.483)	(.479)	(.485)	(.487)
Observations	5,489	1,851	3,638	3,594	5,616	1,843	3,773	3,743	11,005	3,694	7,411	7,337
Self-confidence(=1)	.286	.279	.289	.291	.26	.251	.264	.26	.273	.265	.277	.276
	(.452)	(.449)	(.454)	(.454)	(.439)	(.434)	(.441)	(.439)	(.445)	(.441)	(.447)	(.447)
Observations	5,489	1,851	3,638	3,594	5,616	1,843	3,773	3,743	11,005	3,694	7,411	7,337
Sense of belonging(=1)	.952	.956	.95	.949	.973	.974	.972	.968	.963	.965	.962	.959
	(.214)	(.205)	(.218)	(.219)	(.163)	(.159)	(.164)	(.176)	(.189)	(.183)	(.191)	(.198)
Observations	3,004	1,021	1,983	1,970	3,390	1,116	2,274	2,267	6,394	2,137	4,257	4,237
Perception of learning	.585	.585	.585	.586	.639	.647	.634	.634	.612	.616	.61	.61
at school(=1)	(.493)	(.493)	(.493)	(.493)	(.48)	(.478)	(.482)	(.482)	(.487)	(.486)	(.488)	(.488)
Observations	5,489	1,851	3,638	3,594	5,616	1,843	3,773	3,743	11,005	3,694	7,411	7,337

Standard deviations in parentheses.

Table 2: The impact of PAE on Non Cognitive Self-assessed Outcomes

	Boys				Girls				Overall			
	OLS		IPWE		OLS		IPWE		OLS		IPWE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Motivation												
Absenteism												
PAE	0.016	-0.017	-0.023	-0.015	0.018	-0.024	-0.028	-0.030*	0.055	-0.072	-0.078	-0.073
	(0.017)	(0.015)	(0.02)	(0.017)	(0.019)	(0.016)	(0.02)	(0.017)	(0.05)	(0.047)	(0.054)	(0.048)
Truancy												
PAE	0.025	0.012	0.009	0.015	0.026	0.007	0.003	0.003	0.05	0.026	0.016	0.023
	(0.017)	(0.017)	(0.019)	(0.018)	(0.020)	(0.019)	(0.022)	(0.020)	(0.069)	(0.042)	(0.045)	(0.041)
Discipline												
Bad Climate												
PAE	-0.025*	-0.027*	-0.035**	-0.033**	-0.018	-0.023	-0.020	-0.019	-0.056*	-0.067**	-0.074**	-0.069**
	(0.014)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.03)	(0.032)	(0.033)	(0.032)
Self-confidence												
PAE	-0.010	-0.011	-0.012	-0.015	-0.014	-0.010	-0.010	-0.007	-0.035	-0.032	-0.033	-0.033
	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.015)	(0.014)	(0.027)	(0.028)	(0.030)	(0.029)
Sense of belonging												
PAE	0.006	0.008	0.006	0.005	0.002	0.005	0.006	0.008	0.043	0.08	0.075	0.082
	(0.008)	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.007)	(0.007)	(0.066)	(0.072)	(0.074)	(0.072)
Perception of learning at school												
PAE	0.001	0.001	0.000	0.006	0.013	0.016	0.013	0.015	0.016	0.031*	0.017	0.028
	(0.013)	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)	(0.013)	(0.013)	(0.017)	(0.017)	(0.021)	(0.019)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,025	10,951	10,979	10,951	11,025	10,951	10,979	10,951	11,025	10,951	10,979	10,951

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E: Cognitive Skills

We use the term final score to refer to the average number of correct answers in the PISA test and not to the actual scores provided by PISA. PISA uses weights based on cognitive response theory. In particular, it uses cognitive item theory and provide several plausible values for each of the competences being evaluated (see OECD, 2012). It is therefore not possible to establish a direct relationship between average number of correct answers in the PISA test and the actual PISA test score. Nevertheless, the correlation between the average number of correct answers and the PISA measures is high, in particular larger than 0.8 and statistically significant at 1% for the three subjects.

Table 1: The impact of PAE on Initial and Final Performance

	OLS		IPWE		NNPS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Initial Performance				
				Level				
PAE	-0.078***	0.026	0.031	0.028	0.063**	0.058***	0.045**	0.035*
	(0.028)	(0.022)	(0.030)	(0.024)	(0.025)	(0.023)	(0.022)	(0.021)
				P25 of the entire sample				
PAE	0.028***	-0.001	-0.001	0.001	-0.010	-0.011	-0.006	-0.005
	(0.009)	(0.008)	(0.011)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
				Final Performance				
				Level				
PAE	-0.103***	0.023	0.041	0.032	0.094***	0.050**	0.047**	0.055**
	(0.036)	(0.028)	(0.040)	(0.029)	(0.027)	(0.024)	(0.023)	(0.022)
				P25 of the entire sample				
PAE	0.031**	-0.012	-0.016	-0.012	-0.031**	-0.013	-0.014	-0.018*
	(0.014)	(0.011)	(0.015)	(0.011)	(0.013)	(0.011)	(0.010)	(0.010)
Controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes
No. matches per obs.	-	-	-	-	2	4	6	8
Observations	11,051	10,977	11,004	10,977	10,977	10,977	10,977	10,977

Results for the complete questionnaire. Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The program increases students' initial score on average, but not in the bottom part of the distribution. Therefore, as the program improves student's rate of decline on average and among those falling behind, it increases students' final score on average and among the poor performing ones.

F: School level analysis

Table 1: Summary Statistics at the school level

Variable	(1) All	(2) Treated	(3) Controls	(4) P-value Diff. (2)-(3)	(5) Weighted Controls	(6) P-value Diff. (2)-(4)	(7) P-score
Individual variables							
Initial test score[a]	.608	.594	.615	.041	.614	.318	yes
	(.096)	(.089)	(.099)		(.071)		
Girl(=1)	.501	.497	.503	.604	.501	.804	yes
	(.123)	(.123)	(.123)		(.091)		
Migrant(=1)	.125	.178	.099	.000	.174	.158	yes
	(.17)	(.204)	(.144)		(.198)		
Repeated once(=1)	.247	.284	.229	.001	.261	.377	yes
	(.144)	(.156)	(.134)		(.102)		
Repeated more than once(=1)	.104	.123	.095	.058	.113	.466	yes
	(.138)	(.143)	(.135)		(.093)		
Attended kindergarden(=1)	.834	.825	.839	.345	.824	.634	yes
	(.138)	(.14)	(.137)		(.122)		
Socioeconomic variables							
Index of education possession[b]	.036	.025	.042	.588	.067	.326	yes
	(.3)	(.295)	(.303)		(.228)		
Mother highly educated(=1)[c]	.327	.288	.346	.001	.299	.792	yes
	(.17)	(.144)	(.179)		(.161)		
School variables							
School size	581.171	597.592	573.115	.461	624.422	.930	yes
	(325.934)	(293.526)	(340.95)		(270.749)		
Prop. of dropout	.103	.126	.092	.006	.119	.706	yes
	(.114)	(.116)	(.118)		(.119)		
Prob. of dropout in	.23	.30	.196	.028	.324	.741	yes
high quartile(=1)	(.422)	(.46)	(.398)		(.469)		
ESCS in high quartile(=1)[d]	.248	.146	.298	.000	.161	.911	yes
	(.432)	(.355)	(.458)		(.368)		
Student-Teacher Ratio	9.441	9.091	9.612	.347	9.304	.654	yes
	(7.048)	(2.159)	(8.471)		(2.18)		
School climate-teacher[e]	.554	.669	.498	.001	.711	.616	yes
	(.498)	(.472)	(.501)		(.454)		
Observations	395	130	265		265		

Standard deviations in parentheses.
[a] Initial test score corresponds to the average score in the first five questions of the first cluster of the test.
[b] The index of education possession indicates whether the home possesses a desk and a quiet place to study, a computer and/or educational software and books to help with school work, and a dictionary. It ranges between -3.93 and 1.12.
[c] The mother is defined as highly educated if she has achieved at least tertiary education.
[d] Index of economic, social, and cultural status.
[e] It is a dummy equal to 1 if the school is below the median value of the index of teacher-related factors affecting school climate. Positive values indicate that the teacher-related behaviors hinder learning to a lesser extent. The index ranges between -3.2778 + 2.8533.

Here we consider the school as the unit of analysis. Recall that to the extent that we cannot observe whether a particular student actually received the treatment or not, we might not capture the true effect of the PAE. Therefore the analysis at the school level is crucial. Before estimating the impact of the PAE on outcomes, we take average of all variables, that is, we *collapse* the data at the school level. We then proceed as in the student analysis above: we estimate the probability of participating in the PAE (the propensity score), use the estimated propensity score to construct the re-weighted sample of control schools, and we use the previous results to compute the inverse probability weighting estimator (with and without covariates). As above, we also provide results for the simple OLS. Notice that, for the impact of the PAE on mean rate of decline, we used weighted averages taking into account the school sample size. School characteristics are comparable between treated and re-weighted sample of control schools, as reported in Table 1.

The outcomes considered are the mean school rate decline and the percentage of students at school with rate of decline in the first quartile of the rate decline distribution (P25).

Table 2: The impact of PAE on Rate decline at the School level

	OLS		IPWE	
	(1)	(2)	(3)	(4)
	Complete questionnaire			
	Level			
PAE	0.020	0.039*	0.043*	0.039*
	(0.021)	(0.022)	(0.023)	(0.021)
	P25 of the entire sample			
PAE	-0.010	-0.015	-0.017*	-0.017*
	(0.009)	(0.009)	(0.010)	(0.009)
Controls	No	Yes	No	Yes
Observations	395	395	395	395

Robust standard errors clustered at the school level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results can be found in Table 2. As it can be observed, they are very similar to those in Table 5 when considering the student as the unit of analysis. The effect of the program on mean rate of decline is between 0.039 and 0.043 of one standard deviation (compared to the 0.04-0.05 interval for the increase at the student level). We find that the percentage of students in the first quartile of the rate of decline distribution declines by 1.7 p.p. (compared to the 2 p.p. reduction at the student level). To conclude, results at the school level are in line to those at the student level.

G: Schools' information on the implementation of the PAE

Table 1: Summary Statistics Schools' information on the implementation of the PAE

Variable	(1) With Information	(2) Without Information	(3) P-value Diff. (2)-(1)
Individual variables			
Initial test score[a]	.594	.597	.857
	(.094)	(.08)	
Girl(=1)	.512	.471	.086
	(.113)	(.136)	
Migrant(=1)	.188	.164	.513
	(.212)	(.194)	
Repeated once(=1)	.295	.262	.259
	(.16)	(.152)	
Repeated more than once(=1)	.108	.147	.255
	(.077)	(.219)	
Attended kindergarden(=1)	.805	.857	.030
	(.151)	(.112)	
Socioeconomic variables			
Index of education possession[b]	.006	.062	.314
	(.297)	(.298)	
Mother highly educated(=1)[c]	.301	.262	.132
	(.149)	(.134)	
Father highly educated(=1)[d]	.291	.265	.361
	(.15)	(.152)	
School variables			
School size	584.893	631.024	.426
	(274.045)	(327.921)	
Prop. of dropout	.125	.126	.984
	(.117)	(.115)	
Prob. of dropout in	.333	.32	.880
high quartile(=1)	(.474)	(.47)	
Prop. of migrants (school)	.189	.164	.504
	(.212)	(.194)	
ESCS[e]	-.397	-.499	.179
	(.406)	(.408)	
ESCS in high quartile(=1)	.202	.073	.029
	(.404)	(.256)	
Student-Teacher Ratio	9.06	9.292	.535
	(2.257)	(1.859)	
Principal enhance school's	.25	.175	.314
reputation(=1)[f]	(.436)	(.378)	
Parental pressure on teachers(=1)[g]	.393	.316	.389
	(.491)	(.468)	
School climate-teacher(=1)[h]	.69	.614	.395
	(.465)	(.493)	
Rural(=1)[i]	.464	.368	.296
	(.502)	(.484)	
Observations	84	44	

Standard deviations in parentheses.
[a] Initial test score corresponds to the average score in the first five questions of the first cluster of the test.
[b] The index of education possession indicates whether the home possesses a desk and a quiet place to study, a computer and/or educational software and books to help with school work, and a dictionary. It ranges between -3.93 and 1.12.
[c] The mother is defined as highly educated if she has achieved at least tertiary education.
[d] The father is defined as highly educated if he has achieved at least tertiary education.
[e] Index of economic, social, and cultural status.
[f] The dummy is equal to 1 if the principal enhances school's reputation on weekly basis.
[g] The dummy is equal to 1 if the principal claims that parents exert pressure into teachers and principal to improve the school quality.
[h] It is a dummy equal to 1 if the school is below the median value of the index of teacher-related factors affecting school climate. Positive values indicate that the teacher-related behaviors hinder learning to a lesser extent. The index ranges between -3.2778 + 2.8533.
[i] It is a dummy equal to 1 if the school is located in a village or a small town.

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