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The heterogeneous effect of information on student performance: Evidence from a randomized control trial in Mexico☆

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ABSTRACT

We use data from the randomized control trial of the *Percepciones* pilot to study whether providing 10th grade students with information about the average earnings associated with different educational attainments, life expectancy, and obtaining funding for higher education can contribute to improving student outcomes. We find that the intervention had no effects on a proxy for on-time high school completion, but a positive and significant impact on standardized test scores and self-reported measures of effort. The effects on standardized test scores are larger for girls and for students from households with relatively high incomes. We also find positive, but not statistically significant effects, on the probability of taking a university entry exam and of obtaining a high score in the exam.

1. Introduction

There is a growing consensus that quality -rather than quantity- of education is an important driver of economic growth (Hanushek and Woessmann 2008, 2012). However, there is much less consensus on what type of interventions can help improve student learning in a cost effective way. Based on the results of rigorous impact evaluations, researchers have identified pedagogical interventions (e.g. adaptive computer based assisted learning and student tracking), individualized teacher training and teacher incentives based on performance[1] as types of interventions that are most likely to improve student learning in developing countries (see Evans and Popova (2015), McEwan (2015) for two recent reviews).[2] Nevertheless, many low and middle income countries do not have the resources to scale up interventions of these types. In this paper we use data from a randomized control trial in urban Mexico to study whether providing 10th grade students with an essentially zero-cost information package on monetary and non-monetary rewards of education can affect their performance in the last year of high school (12th grade), and in a university entry exam.

Evidence from developing countries shows that providing information about the labor market returns to different education levels can improve students' attainment in basic education (Jensen, 2010). Informing students about the monetary benefits and the costs of attending university - both on average and for specific fields - can have significant effects on educational choices both in developed countries (Wiswall and Zafar, 2015; Bettinger et al., 2012) and developing coun-

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[1] Banerjee et al. (2007) find that in urban India a computer-assisted learning program focusing on math increased math scores by 0.47 standard deviations. Duflo et al. (2011) find that that a tracking program in Kenya that sorted students based on their prior achievements led to improvements in test scores both among students of high ability (0.19 standard deviations) and low ability (0.16 standard deviations). Glewwe et al. (2010) and Muralidharan and Sundararaman (2011) document the effectiveness of performance based incentives for teachers on students' test scores in Kenya and India respectively.

[2] Fryer (2016b) reviews the evidence from randomized field experiments that evaluate policies to improve human capital in developed countries.

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tries (Hastings et al., 2015; Delavande and Zafar, 2014; Dinkelman and Martínez, 2014; Rao, 2016; Bonilla et al., 2017). However, there is very limited evidence that information about the returns to human capital can have long term impacts on student learning (Fryer, 2016a).[3] In principle, information interventions that are able to increase students' effort have the potential to improve their performance if school performance responds to changes in effort.

Mexico, like many other middle-income countries, has reached almost universal enrollment rates in primary and lower secondary schools, but still faces important challenges in the education system. Only six out of every ten students who enroll in high school graduate on time. Among those who reached 12th grade in 2008, only 15.6 percent scored good or excellent in a census based nationally standardized assessment of math skills - *Evaluación Nacional de Logro Académico en Centros Escolares* (ENLACE), as opposed to 52.3 percent scoring good or excellent in Spanish. Previous research for Mexico has highlighted that financial incentives have the potential to reduce the achievement gap in high school.[4] Nevertheless, it is unclear whether individual constraints, other than the financial ones, can affect student performance.

In 2009 the Mexican Secretariat of Public Education (SEP for its acronym in Spanish), attempting to improve on-time graduation and learning outcomes in high school, designed and piloted an intervention aimed at students entering 10th grade. It provided them with a range of gender-specific information about the average earnings associated with completion of high school and university education, as well as about their life expectancy and funding opportunities they might tap to attend higher education. Known as *Percepciones*, the pilot program included an evaluation strategy based on a stratified randomized control trial (RCT), with 26 schools assigned to the treatment group and 28 to the control group. In November 2009, the baseline data was collected and the information treatment was delivered. Using 2012 and 2013 administrative data from the 12th grade census-based nationally standardized ENLACE exam and the university entry exam EXANI-II, that is required by a large share of public universities, we measure the impact of the information treatment on a proxy for completing high school on time, on standardized test scores in math and language (Spanish) at the end of high school, and on a proxy for university enrollment.[5] The information from a survey that was administered to a random sample of ENLACE exam takers allows us to study how the intervention changed students' beliefs about returns and some of their behaviors during high school.

At the baseline students on average underestimate the average earnings associated with the completion of high school. On the other hand, the average expected earnings associated with university completion and life expectancy are higher than the observed values. Our results show that, almost three years after the treatment was implemented, both boys and girls in the treatment group are more likely to have updated their beliefs about the average earnings associated with high school completion. The information package had no impact on the proxy for completing high school on time, but had a sizeable and statistically significant effect on the *ENLACE* test score—0.22 standard deviations (σ). The effect on test scores is larger for girls than boys, and we explain it with the fact that girls report higher levels of effort than boys. We test whether the gender-differentiated effect is driven by differences in time preferences (willingness to put off rewards in the present for larger ones in the future), gender-specific responses from parents or teachers, or differential changes in aspirations. We do find evidence consistent with the latter hypothesis since girls in the treatment group are less likely to have ever been married and they report higher education aspirations. We also find evidence of treatment heterogeneity along other dimensions: academic readiness and household socioeconomic status. All students, irrespective of their initial conditions, increase their level of effort but only those who have relatively strong academic skills and high socio-economic backgrounds are able to translate this increased effort into improved learning outcomes. Since students with weak academic and socioeconomic background have the highest risk of dropping out, the complementarity between effort and initial conditions is likely to explain why the intervention did not affect on-time completion. We also find positive, but not statistically significant effects on the probability of taking the EXANI-II and, conditional on taking the exam, obtaining a high score, thus pointing to a potential improvement in the average university readiness.

This paper provides two main contributions. First, although the experiment was not designed to separately identify the effect for boys and girls, this is the first study to report the effects of an intervention that provides gender specific information about the average benefits associated with different levels of education. In many disadvantaged contexts educational choices made by girls are likely to be affected by social norms, rather than potential labor market outcomes.[6] We found that interventions such as *Percepciones*, by changing girls' intrinsic motivation and aspirations, can be an effective way of changing girls' educational choices, and improving their learning outcomes. Our result is of particular interest for the literature that studies gender differences in educational choices (Fortin et al., 2015) and learning outcomes (Guiso et al., 2008).

The second contribution of this study consists of highlighting that information interventions, although they have virtually zero cost, can improve learning outcomes through the cumulative effect on student behaviors. At the same time they can exacerbate existing socioeconomic inequalities. The last result suggests that a more equitable improvement in learning can be achieved by complementing information based interventions with measures that attenuate differences in initial conditions.

The paper is organized as follows. Section 2 presents general information regarding the high school and university education system in Mexico and a description of the information treatment within the *Percepciones* project. In Section 3 we discuss the possible mechanisms through which the *Percepciones* intervention can increase student effort and we provide a simple framework to understand under what conditions an increase in effort can result in improved student performance. The econometric model and the main results are presented in Section 4. Potential explanations for the treatment heterogeneity in high school performance are discussed in Section 5. Finally, Section 6 concludes.

2. Context and intervention

2.1. Context

The high school (upper secondary) education (*Educación Media Superior* or EMS for its acronym in Spanish) system in Mexico has 4.1 million students, typically between 15 and 18 years old, in grades 10th,

[3] Recent evidence (Cunha et al., 2017; Bergman, 2017) finds that providing parents with information about student grades and attendance increases student test scores.

[4] Behrman et al. (2015) compare three different types of performance based incentives in a sample of schools with characteristics similar to the ones involved in our study and they find evidence that a combination of financial incentives both for students and teachers was the most effective, increasing standardized test scores by 0.6 standard deviations compared to the control group.

[5] An intermediate survey at the end of the 2009–2010 school year had been planned, but due to changes in the ministry's management there was no funding available.

[6] Attanasio and Kaufmann (2012a) found for Mexico that educational choices of boys are more likely to be correlated with expectations concerning the labor market returns of higher education than girls' expectations, which display a stronger correlation with marriage market considerations. Kaufmann et al. (2013) use data from Chile to show that being admitted to a higher ranked university has substantial returns in terms of partner quality for women.

11th and 12th. EMS is offered by four different providers: 1) the federal government (accounting for 26 percent of total enrollment), 2) the state government (43.8 percent), 3) publicly-financed autonomous universities (12.5 percent), and 4) private entities. EMS offers three types of degree programs: *general*, which prepares students for higher education; *technological* which prepares students both for the labor market and higher education, and *technical*, which emphasizes technical and vocational education. According to the official statistics from SEP in 2013, only 61 percent of students graduated in the normal three years after enrolling. On-time graduation rates vary across types of degree programs with *general* schools showing the highest (64 percent), followed by *technological* schools with rates very close to the national average and *technical* schools showing the lowest (48 percent). Technological schools produce on average 30 percent of the Mexico high school graduates and together with general schools they make up to 90 percent of the high school graduates. In Table AI we compare the characteristics of 12th grade students who graduate from the three different high school types in 2009 using the *ENLACE de contexto* (described in section 3.3.1). Students attending technological schools in urban areas (the universe from which our sample was drawn) display levels of preparedness in math and Spanish that are comparable to those attending general schools, but slightly worse socioeconomic conditions. Students from general and technological schools also display similar expectations in terms of future earnings upon high school completion (Fig. AI).

The EMS system is characterized by strict promotion criteria. Students must pass five out of eight disciplinary subject areas and practical modules. Otherwise they have to repeat the semester. Students who fail three or fewer subject areas can enroll in the next semester but they have to attend and pass intensive courses (the so called *regularizacion*) during a fixed time window. In addition, students must satisfactorily complete all their subject areas and modules within at most ten semesters after enrolling in EMS. Otherwise they lose the right to re-enroll. Partly as a result of the strict promotion rules, there are very high grade repetition and subject repetition rates, 15.3 percent and 31.3 percent respectively in 2013.[7] According to the 2009 Survey of Early Dropouts (*Encuesta Nacional de la Deserción en la Educación Media Superior*) repetition is the second most common reason - after financial constraints - mentioned for early dropout.[8] In 2013, 14.5 percent of enrolled students dropped out of high school, on average.

Household level data show that in 2013 the gross enrollment rate in higher education was 29 percent, with roughly three quarters of the students attending public institutions, which are free of charge. More than 90 percent of the students who enroll in higher education choose four/five year university programs, with the remaining 10 percent opting for short cycle technical or vocational programs. Higher education institutions have different admission criteria, which may include an exam. Most public institutions use the results of an entry test, the *Examen Nacional de Ingreso a la Educación Superior* (EXANI-II), discussed in section 3.3.2, while "elite" institutions (such as the *Universidad Nacional Autonoma de México*) have open admission (*pase automatico*) for the highest-GPA graduates from the equally selective high school associated with the higher education institution.[9]

2.2. Description of the intervention and evaluation design

The *Percepciones* pilot took place in 54 technological high schools run by the Federal Government. The technological schools run by the Federal Government are typically large (930 students on average) and they can belong to different subsystems depending on their specialization: industrial (DGETI), agricultural (DGETA) and ocean-related (DGCYTM). The design of the intervention benefited substantially from a survey conducted in 2005 as part of the evaluation of the Mexican program *Jóvenes con Oportunidades*. The 2005 survey showed that students tended to misperceive the returns to education as compared to the actual returns revealed in the labor survey ENOE (*Encuesta Nacional de Ocupación y Empleo*), and the misperceptions were particularly high among girls.[10]

An interactive computer software, designed explicitly for the *Percepciones* project, gathered information on students' perceived returns to schooling and, in the case of the treatment group, provided the information package. In order to elicit the individual beliefs about their own earnings upon completing subsequent school levels (lower secondary/high school/university), the computer software used three subjective expectation questions, similar to the ones included in the *Jóvenes con Oportunidades* survey. Similarly, the computer software elicited information about the students' perception about the earnings associated with different school levels for an average person, as opposed to expectations about his or her own returns. The exact questions are reported in appendix A.1.

Students in the treatment group received three main categories of information. First, they were given gender-specific information on the monetary benefits of educational achievements, as computed using data from ENOE for the second quarter of 2009. The information was given in the form of (a) level of monthly wages in pesos for each educational attainment, (b) additional monthly pesos earned working full time by completing an additional educational level, (c) the net present value of the additional income flows assuming entry and exit to the labor market at ages 25 and 65, respectively. The original statements for high school and university are reported in appendix A.2.[11]

The second category of information described a higher education scholarship program run by the federal government, known as *Pronabes*. This program targets student from households with a monthly income equal to or below three minimum wages, and provides grants that vary between $750 MX and $1000 MX per month for the entire length of the higher education course. These amounts are relatively large, since they vary in a range between 15 and 20 percent of the average monthly salary that a graduate from a technological school would earn upon entering the labor market. The scholarship is unconditional during the first two years, but depends on academic performance afterwards.

The third category of information concerned life expectancy differentiated by gender. Based on the results of early theoretical work (Becker, 1975; Ben-Porath, 1967) and more recent empirical evidence (Jayachandran and Lleras-Muney, 2009), longer life expectancy should encourage human capital accumulation, since a longer time horizon increases the value of investments that pay out over time.

On average, students in the treatment group spent 12 min interacting with the interface. In addition, students in the treatment group viewed a 15-s video conveying the message that youth can empower themselves with education. Teachers were not exposed to the treatment.[12]

[7] Students who fail three or more subjects for two consecutive semesters have to repeat the entire grade.

[8] Jacob and Lefgren (2009) use a plausibly exogenous variation in retention generated by a test-based promotion policy in the US to show that retaining low-achieving eighth grade students in elementary school substantially increases the probability that these students will drop out of high school.

[9] Elite private institutions have admission tests and a high school GPA requirement. Non-selective private institutions do not have admission tests.

[10] See Attanasio and Kaufmann (2012b) for a detailed description of the expectations module included in the *Jóvenes con Oportunidades* survey.

[11] The statements about the earnings for lower secondary, high school and college graduates have to be interpreted as simple associations, whereas the belief questions are implicitly asking about the causal relationship between education attainments and future earnings.

[12] Each school had a program representative, usually the representative of *Construye-T*, a federal program that has the objective to improve students' socioemotional skills.

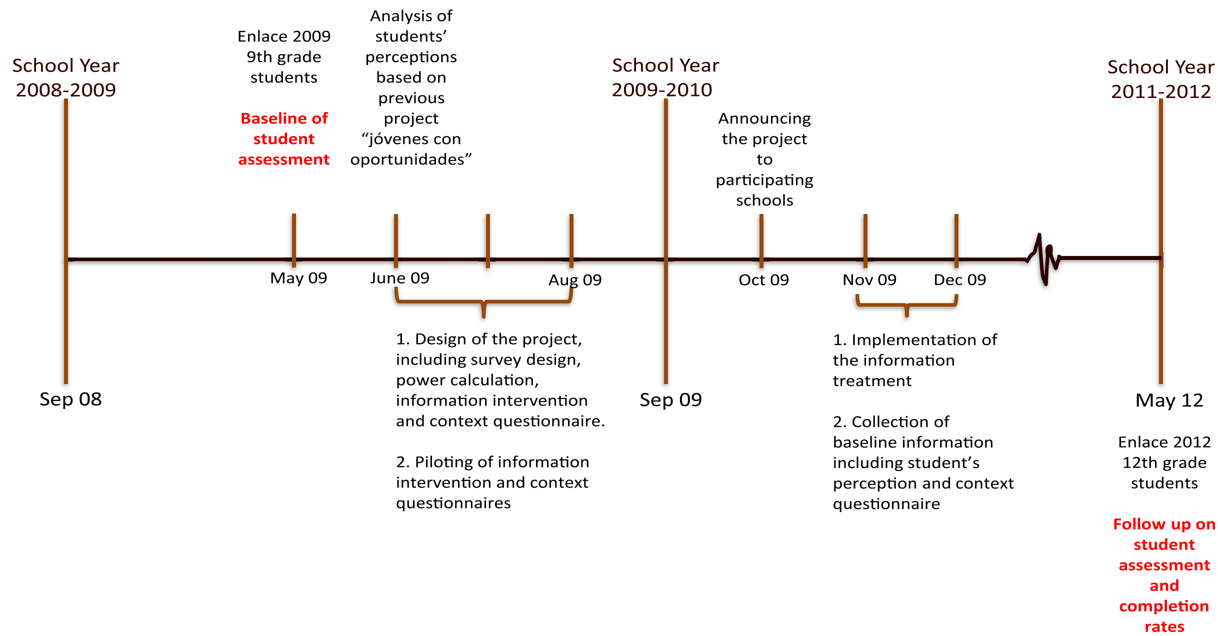


Fig. 1. Timeline of the *Percepciones* project.

A randomized control trial was designed to evaluate the impact of the intervention. Fig. 1 shows the time line of the project spanning from May 2009 to May 2012. The design of the intervention, randomization, and sampling took place between June and August 2009. Following a two-step stratified sampling by regions (north, center, and south), the 54 schools were randomly divided into 26 treatment schools and 28 control schools. The selected schools had an average of eight classrooms in 10th grade, with around 40 students in each classroom. For each school, at least two 10th grade classrooms were randomly selected to participate in the pilot. In total, 111 classrooms and 4145 students took part in the experiment.[13] All students in the sample were administered a sociodemographic survey in their own classrooms. A randomly selected subsample of 3502 students (84 percent of the original sample) was then conducted to the school computer laboratories where PCs had been preloaded with a computer software that will be described in the next section.[14]

Most of the interventions that have been previously tested provide information either on the expected financial returns of education (Jensen, 2010) or on the sources of financial aid (Dinkelman and Martínez, 2014).[15] The *Percepciones* project gave students an information package covering both types of information, plus predictions concerning life expectancy. The intervention's design does not allow us to assess of whether our results are driven by any specific piece of information or by the entire package.

[13] In two schools the first two randomly selected classrooms were too small, requiring selection of two additional classrooms.

[14] The selection was made necessary in some of the schools because either the number of available computers was lower than the number originally communicated to the ministry or some of the computers were malfunctioning. The use of the school computers was meant to assess the scalability of the intervention nationwide.

[15] An exception is McGuigan et al. (2012) that tests the impact of a large set of information about the benefits and costs of university on the perceptions of high school students in the UK.

3. Conceptual framework and data

3.1. Conceptual framework

Percepciones provided no direct information on the linkage between student performance and earnings.[16] This section aims to highlight how the interaction between the information provided in 10th grade and the institutional features of the Mexico's school system have the potential to increase student effort. We also study under what conditions an increase in effort can lead to improvements in student outcomes. For this purpose, we use a simple education production function, where school performance S at time t is a function (f) of the student's effort (e) and a set of predetermined characteristics (K_0), that include, among others, student readiness, parental education, household income, and neighborhood characteristics:

$$S_{i,t} = f(e_{i,t}, K_{0i}) \tag{1}$$

Mirroring Fryer (2016a), we assume that a) f is twice continuously differentiable in e and K_0, b) the first derivatives of S with respect to e and K_0 are both positive; b) f exhibits diminishing marginal returns to e. Exerting effort implies a cost, determined by the function $C_{i,t} = C(e_{i,t}, X_{it})$, where X_{it} includes all those factors that might affect the opportunity cost of exerting effort in school, such as the potential wage that students might earn by dropping out of school (with higher wage implying a higher opportunity cost of staying in school) and the availability of scholarships (that would reduce the opportunity cost).

If future labor market outcomes are positively linked to school performance, the optimal level of effort will be such that the discounted value of the expected marginal return to a unit of effort in terms of future earnings is equal to its marginal cost (see Fryer (2016a)). Using this simple framework, we next discuss how *Percepciones* might change the probability of completing high school on time, the results in a standardized test at the end of high school, and the probability of enrolling in university.

[16] When the intervention was designed ENLACE had been in place for only two years, thus making impossible to provide information on the link between the ENLACE outcomes and earnings.

High School Performance: When starting high school, K_{0i} is given and it can not be altered by the intervention. A change in individual effort is the only channel through which *Percepciones* can affect high school on-time completion and learning outcomes. If the average 10th grade student is expecting that high school graduation will bring earnings that are lower than the true ones, or her life expectancy to be shorter than the true one, the provided information should cause her to revise her beliefs upward. When promotion rules are not particularly strict and grade repetitions rates are low, an update in the beliefs might not necessarily be associated with changes in student effort. However, as highlighted in section 2.1, promotion rules in the Mexican high school education system are strict and repetition rates are high. Therefore, the cost of not exerting the sufficient amount of effort is particularly high. The extent to which e affects S depends on whether e and K_0 are complements or substitutes in the production function in eq. (1). If e and K_0 are complements, only students with a certain level of initial conditions will be able to translate increased effort into increased on time completion and better test scores. However, the effect on the latter crucially depends on the *selection* effect. If more students are completing on time as result of the intervention, there might be an increase in the share of academically weak students who seat the ENLACE exam and they can eventually lower the average score.

University Enrollment: Besides the change in beliefs there are two additional channels through which the *Percepciones* pilot could potentially affect the probability of enrolling in university: a) a reduction in the perceived $C_{i,t}$ driven by provision of information about the *Pronabes* scholarship, and b) a change in K_0 when entering higher education as a result of changes in effort during high school. If at the baseline students were underestimating the earnings associated with high school and university completion and they were not aware of the *Pronabes* scholarship, the *Percepciones* will unambiguously lead to an increase in the probability of enrolling in university driven by an increase in the contemporaneous level of effort (e_{it}), an increase in the level of university readiness (K_{0i}) induced by a higher level of effort in high school, and a reduction in the opportunity cost ($C_{i,t}$). The effect of information provision is theoretically ambiguous for those who were overestimating the benefits of university completion and underestimating the benefits of high school completion at the baseline. In fact, in this case, the potential negative effect driven by the reduction in contemporaneous effort might be more than offset by the improvement in university readiness and the reduction in the opportunity cost. Similarly the effect is ambiguous for those who were underestimating the benefits of university completion and overestimating the benefits of high school completion at the baseline, as they might have lower university readiness although they have increased incentives to enroll in university. For those who were overestimating earnings associated both to university and high school completion, the intervention will lead to a reduction in university enrollment, unless there is a sufficiently large share of individuals who change their enrollment decision after knowing about *Pronabes*.

In summary, depending on the baseline distribution of beliefs, there is a potentially large share of students for which the effect of *Percepciones* on university enrollment is theoretically ambiguous. If a student does not know the function f or she is present biased, she will not change her effort irrespective of how biased her initial beliefs are.

3.2. Baseline characteristics

At the baseline, we measured student socioeconomic characteristics, their inter-temporal preferences and their academic readiness.

In order to measure student socioeconomic characteristics, we rely on the survey administered to the students in November 2009, just before the treatment was rolled out. Students in treatment and control schools were asked, among other things, questions about the sources of their information about returns, and about their household income, using a set of pre-specified brackets.[17] Students were also asked about parents' education and work status. The baseline survey also included a module that elicits students' inter-temporal preferences: respondents were asked to make a choice in a hypothetical situation in which they are offered a certain amount of money that can be cashed in now, or can be cashed in later for a larger sum.

We use administrative data on 9th grade ENLACE scores in math and language to measure students' readiness before entering high school. From 2007 to 2013, ENLACE was administered to all students in the 3rd to 9th and 12th grades. The test is voluntary and has no effect on graduation or a student's GPA. The exam is administered in the students' schools by outside proctors. The score is normalized to have a mean of 500 and a standard deviation of 100. In appendix B.1 we provide details on how we merge the information from the baseline survey with the 9th grade ENLACE test from the years 2008 and 2009.

Table 1 shows the baseline characteristics for the full sample as well as separately for boys and girls, distinguishing between students in the treatment and control groups. In the top panel we report the socioeconomic characteristics measured through the baseline survey, and in the bottom panel the administrative information on 9th grade test scores. Overall, the characteristics of the treatment and control group seem well balanced in line with the randomized design of the evaluation. Fathers tend to be more educated and more likely to work than mothers. Self-reported measures of effort do not display major differences between boys and girls, nor do the number of hours spent doing homework (5.62 for boys and 5.11 for girls) or the number of school days missed in the previous month (2.8 both for boys and girls). Girls report a much lower probability of having failed at least one subject in lower secondary school than boys (19 percent versus 30 percent).

Students in our sample were supposed to take the 9th grade ENLACE test in Spring 2009. However, there is a relatively small share of students who had taken the test in 2008. The latter are either repeaters or students who had taken a gap year before enrolling in high school. When we look at the take up rate separately for year 2009 and 2008, we do find larger values for the treatment than the control group, but the differences are not statistically significant at conventional level (see Table 1). Nevertheless, the combined take up rate of the 9th grade exam is statically larger (p-value = 0.07) for the treatment than the control group (78 percent versus 72 percent). In order to account for the potential consequences of this imbalance, all our specifications will include a dummy for whether the individual has the 9th grade information missing. The average 9th grade scores in math and Spanish are not statistically different for students in treatment and control schools.

In 9th grade, girls perform better than boys in language, and girls do as well as boys in math (approximately 35 percent of them are classified as insufficient). Previous work using data from low- and middle-income countries shows that the gender gap in math is present as early as 4th grade (Bharadwaj et al., 2012). This is not true for Mexico. In order to assess whether our sample is representative of the Mexican population, we follow the nationwide cohort of 6th grade ENLACE takers in the year 2007 over to 9th grade in 2010 and 12th grade in 2013. Girls do consistently better than boys in language and the gap stays constant throughout the different grades. Neither in 6th grade nor in 9th grade is there evidence of a gender gap in math, but girls' average 12th grade score in math is 30 points—0.30σ—lower than boys' (Table AII). The gender

[17] Information regarding household income was reported in brackets as follows: 1) less than \$1500 MX, 2) between \$1501 and \$3500, 3) between \$3501 and \$7,000, 4) between \$7001 y \$10,000, 5) between \$10,001 and \$15,000, 6) \$15,001 y \$25,000, 7) more than \$25,000 MX. Information about household income was not reported by 14 percent of the students, but the attrition rate is not statistically different for the treatment and control group.

Table 1
Baseline characteristics by Treatment status.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Full Sample						Boys						Girls					
	Treatment		Control		T = C	N	Treatment		Control		T = C	N	Treatment		Control		T = C	N
	Mean	SD	Mean	SD	p-value		Mean	SD	Mean	SD	p-value		Mean	SD	Mean	SD	p-value	
Panel A: Baseline Survey																		
Male	0.52	0.50	0.51	0.50	0.748	4145												
Age	16.49	0.93	16.50	0.79	0.940	4145	16.56	0.98	16.59	0.88	0.778	2142	16.41	0.87	16.40	0.66	0.866	2003
HH Members	5.16	1.74	5.23	1.76	0.526	4141	5.17	1.75	5.20	1.64	0.736	2140	5.16	1.74	5.27	1.87	0.421	2001
Father works	0.84	0.37	0.85	0.36	0.525	4145	0.87	0.34	0.86	0.35	0.438	2142	0.81	0.39	0.84	0.36	0.163	2003
Mother works	0.48	0.50	0.45	0.50	0.260	4145	0.46	0.50	0.44	0.50	0.485	2142	0.51	0.50	0.47	0.50	0.160	2003
Father with primary ed.	0.29	0.45	0.32	0.47	0.448	3837	0.26	0.44	0.30	0.46	0.432	1988	0.31	0.46	0.34	0.47	0.554	1849
Mother with primary ed.	0.30	0.46	0.34	0.47	0.357	4018	0.28	0.45	0.33	0.47	0.308	2059	0.33	0.47	0.35	0.48	0.474	1959
Father with secondary ed.	0.36	0.48	0.37	0.48	0.813	3837	0.37	0.48	0.37	0.48	0.844	1988	0.36	0.48	0.37	0.48	0.835	1849
Mother with secondary ed.	0.39	0.49	0.42	0.49	0.283	4018	0.40	0.49	0.40	0.49	0.684	2059	0.39	0.49	0.43	0.50	0.191	1959
Father with high school or higher	0.35	0.48	0.31	0.46	0.338	3837	0.37	0.48	0.33	0.47	0.338	1988	0.33	0.47	0.29	0.45	0.410	1849
Mother with high school or higher	0.30	0.46	0.24	0.43	0.118	4018	0.32	0.47	0.27	0.44	0.187	2059	0.29	0.45	0.22	0.41	0.115	1959
Heater	0.66	0.47	0.60	0.49	0.333	4145	0.70	0.46	0.60	0.49	0.145	2142	0.62	0.49	0.60	0.49	0.706	2003
Washing Machine	0.80	0.40	0.78	0.42	0.677	4145	0.82	0.38	0.80	0.40	0.484	2142	0.76	0.42	0.76	0.43	0.877	2003
PC	0.61	0.49	0.52	0.50	0.122	4145	0.63	0.48	0.55	0.50	0.125	2142	0.58	0.49	0.49	0.50	0.154	2003
Internet	0.44	0.50	0.35	0.48	0.142	4131	0.46	0.50	0.38	0.49	0.201	2138	0.43	0.49	0.33	0.47	0.125	1993
Average Share of homework handed in	0.83	0.19	0.81	0.20	0.170	4120	0.81	0.19	0.78	0.20	0.037	2129	0.85	0.19	0.84	0.19	0.664	1991
School days missed last month	2.58	2.30	2.79	2.41	0.158	1418	2.70	2.39	2.80	2.42	0.644	732	2.45	2.20	2.78	2.41	0.132	686
Secondary school qualification	8.52	0.81	8.44	0.82	0.326	4067	8.37	0.82	8.24	0.80	0.120	2103	8.68	0.78	8.65	0.79	0.698	1964
Failed any subject in sec. school	0.23	0.42	0.24	0.43	0.569	4133	0.29	0.45	0.30	0.46	0.810	2137	0.17	0.37	0.19	0.39	0.331	1996
Panel B: 9th grade ENLACE Outcomes																		
ENLACE in 2009	0.71	0.45	0.66	0.48	0.177	4145	0.66	0.47	0.63	0.48	0.582	2142	0.76	0.43	0.68	0.47	0.069	2003
ENLACE in 2008	0.07	0.25	0.05	0.22	0.189	4145	0.09	0.28	0.06	0.23	0.057	2142	0.04	0.21	0.05	0.21	0.886	2003
Language Score	532.57	98.84	524.23	96.52	0.522	3114	516.95	97.39	506.68	96.92	0.404	1572	548.54	97.80	542.06	92.83	0.680	1542
Language Insuff.	0.26	0.44	0.27	0.45	0.804	3114	0.31	0.46	0.34	0.47	0.610	1572	0.21	0.41	0.21	0.41	0.906	1542
Math Score	541.81	103.99	529.03	97.35	0.343	3114	537.51	104.13	525.47	98.96	0.365	1572	546.21	103.72	532.66	95.62	0.380	1542
Math Insuff.	0.46	0.50	0.50	0.50	0.488	3114	0.47	0.50	0.51	0.50	0.446	1572	0.45	0.50	0.48	0.50	0.591	1542

Note: We report the mean of each variable, its standard deviation in parentheses, the p-value on the difference between T and C and the number of observations. The p-value on the test of equality is based on an OLS regression of the outcome of interest regressed on the treatment dummy and the strata dummies, with standard errors clustered at school level.

Table 2
Correlation between 12th grade ENLACE scores and medium term outcomes.

Outcome Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	University (Y/N)				NEE (Y/N)				Unemployed (Y/N)			
Spanish	0.125***	0.122***			−0.029***	−0.031***			−0.007	−0.008*		
	(0.008)	(0.008)			(0.005)	(0.005)			(0.004)	(0.004)		
Math			0.116***	0.105***			−0.040***	−0.030***			−0.005	−0.008**
			(0.007)	(0.007)			(0.004)	(0.004)			(0.004)	(0.004)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	3552	3492	3552	3492	3500	3492	3500	3492	3500	3492	3500	3492
Mean Dep. Var.	.691	.691	.691	.691	.0883	.0883	.0883	.0883	.0469	.0469	.0469	.0469
Adj. R^2	.0625	.121	.0695	.117	.00838	.0557	.0216	.0574	.000537	.00391	.000432	.00414

Note: The sample include the matched individuals aged 18–20 who took the 12th grade ENLACE exam over the period between 2008 and 2010 and were interviewed in the 2010 ENILEMS high school graduates survey. The dependent variables are the dummy variables for whether the high school graduate in 2010 was enrolled in university, “Not in Education, or Employment” (NEE), unemployed. The controls include age, dummies for gender and being in a urban area, and states of birth.

gap in 12th grade may be partly explained by differential selection: 28.6 percent of the boys who took the ENLACE in 6th grade in 2007 completed the 12th grade exam in 2013, as opposed to 34.9 percent of the girls.

3.3. Outcome measures

3.3.1. ENLACE 12th grade

Students enrolled in 10th grade in 2009 were supposed to complete high school in 2012.[18] We use data from the 2012 12th grade ENLACE exam to measure the three main outcomes of interest: the probability of taking the test, math scores, and Spanish scores. The 12th grade test is given to students who are on track to graduate at the end of the academic year, and previous work (Dustan et al., 2017) has found that it is a good proxy for the probability of completing high school on time. In our sample 61 percent of the students who were surveyed at the baseline took the 12th grade ENLACE exam three years later. There are four possible explanations for why a student who was enrolled in EMS in 2009 did not take the 12th grade ENLACE exam in 2012: (1) the student dropped out of school at some point between 9th and 12th grade, (2) the student repeated one or more semesters, (3) the student did not show up for the exam but regularly completed the EMS, or (4) or potential merging problems. In appendix B.2 we discuss the extent to which each of these four explanations might account for the attrition rate and we conclude that students dropping out of school represents the most quantitatively relevant. Therefore, we interpret the difference in probability of taking the 12th grade exam between the treatment and control groups as a good measure of the intervention’s effect on the probability of finishing high school on time.

The ENLACE score has no bearing on graduation or university admissions and the results do not affect the funding received by the schools. Therefore, as discussed in previous work (Dustan et al., 2017; Avitabile et al., 2015), there is little incentive for score manipulation. Nevertheless, among students who are enrolled in the second semester of 12th grade, the share of those who take the test is extremely high (above 90 percent nationwide). In order to assess how well the results in the ENLACE exam predict future outcomes, we merged the universe of 12th grade ENLACE data from 2008, 2009 and 2010 with data from the *Encuesta de Insercion en el Mercado Laboral* or ENILEMS, a special module of the ENOE, which in 2010 collected information on the academic and labor trajectories of the 18–20 year old high school graduates. In Table 2 we find that both the scores in math and Spanish display a positive and significant correlation with the probability of being enrolled in university, and a negative correlation with the probability of being a so-called “Not in Education, or Employment” (NEE) and of being unemployed. Although it is a low-stakes exam, the ENLACE scores are highly predictive of the future academic performance and labor market outcomes of high school graduates.

A random sample of 20 percent of the ENLACE takers are administered a survey, the so called *ENLACE de contexto* that elicits a broad set of information about student sociodemographic characteristics, such as marital status, as well as student effort and track specific trajectories during high school. The 2012 survey gathers, among other things, information on the student’s expected monthly earnings at ages 30 to 40 based with a completed high school degree, and on a large set of behavioral responses related to student effort, family formation and aspirations. Additional details on the information elicited by the *ENLACE de contexto* that is relevant for our analysis is provided in appendix B.2.

3.3.2. EXANI-II

Individual level information on university enrollment is not collected at central level in Mexico. In order to assess whether *Percepciones* had an impact on a proxy for university enrollment we use information about EXANI-II, a test developed by *Centro Nacional para la Evaluación de la Educación Superior* (CENEVAL)–a not-for-profit private entity whose main objective is to develop tools to evaluate students’ proficiency level. The main objective of the test is to evaluate fundamental skills among university candidates, irrespective of the subject area they are planning to study.

The use of EXANI-II as a selection criteria for university candidates is not mandatory, but over time most major public universities which face an excess demand, have been adopting EXANI-II as one of the selection criteria. In appendix B.3 we discuss the contents of the exam, and the nation-wide figures on university enrollment and the number of EXANI-II takers for the years 2012 and 2013, that are the most relevant for the students in our evaluation sample. In both years, more than 70 percent of the students who enrolled in public universities took EXANI-II. The score varies between 700 and 1,300, and students who score 1150 or above are classified as outstanding.

3.4. Baseline perceptions

As discussed in section 2.2, a random subsample of 3502 (out of 4145) students took a computer-based survey that elicited both the student’s own expected earnings and the student’s expected earnings for the average person. Table AIV suggests that the characteristics of students who took the survey in treatment and control schools are on average the same.

While variation in the perceived earnings for oneself reflects both possible misperceptions about the returns to education and heterogene-

[18] The northern State of Nuevo León is an exception because public high schools follow a two-year program.

Table 3
Baseline beliefs by treatment status.

Variable	(1) Boys	(2)	(3)	(4)	(5)	(6)	(7)	(8) Girls	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Treatment			Control			T = C	Treatment			Control			T = C	Boys = Girls
	Mean	SD	Coeff. Var.	Mean	SD	Coeff. Var.	p-value	Mean	SD	Coeff. Var.	Mean	SD	Coeff. Var.	p-value	p-value
Earnings															
Expected (Self) with Upper Sec.	5823.32	5206.28	89.40	5670.20	5245.97	92.52	0.71	4363.74	4302.50	98.60	4225.35	3978.80	94.16	0.86	0.00
Expected (Others) with Upper Sec.	4690.66	3903.49	83.22	4482.16	3957.35	88.29	0.88	3435	3268.93	95.17	3208.93	3076.06	95.86	0.41	0.00
Measured Average	6436							4827							
Expected Earnings (Self) with University	14403.70	15017.42	104.26	13371.30	14312.27	107.04	0.77	11507.66	13556.53	117.80	11912.79	14617.58	122.70	0.60	0.06
Expected Earnings (Others) with University	12947.35	12096.12	93.43	11998.83	11870.41	98.93	0.56	10186.70	10974.95	107.74	9737.75	11027.41	113.24	0.67	0.00
Measured Average	10974							8522							
Returns															
Implied (Self) Perceptions to Upper Sec.	2923.02	3637.91	124.46	2716.17	3649.04	134.35	0.79	2227.08	3339.73	149.96	2096.04	3228.43	154.03	0.63	0.00
Implied (Others) Perceptions to Upper Sec.	2409.29	2958.41	122.79	2221.02	2859.08	128.73	0.61	1732.90	2383.09	137.52	1621.00	2316.77	142.92	0.53	0.00
Measured Average	1635							1647							
Implied (Self) Perceptions to University	8580.38	12742.56	148.51	7701.09	11771.87	152.86	0.63	7143.92	11760.48	164.62	7687.44	13046.04	169.71	0.47	0.98
Implied (Others) Perceptions to University	8256.68	10443.22	126.48	7516.67	9873.64	131.36	0.50	6751.70	9708.15	143.79	6528.83	9478.14	145.17	0.79	0.05
Measured Average	6143							5343							
Life Expectancy															
Perceived	80.67	14.04	17.40	79.92	14.47	18.10	0.59	78.93	15.00	19.00	80.12	15.57	19.43	0.11	0.80
Measured	72.90							77.6							

Note: We report the monthly mean of each variable expressed in \$ MX, its standard deviation (SD) and the coefficient of variation (Coeff. Var.). The p-value on the test of equality is based on an OLS regression of the outcome of interest regressed on the treatment dummy and the strata dummies, with standard errors clustered at school level. In order to compute the statistics, the top 2% and the bottom 2% of the beliefs distribution have been winsorized. The p-value on the test of equality of boys and girls is based on a *t*-test restricted to boys and girls in the control group. When using *Self* we refer to the earning that the respondent expects for herself/himself when aged between 30 and 40. When using *Others* we refer to the earning that the respondent expects for the average person when aged between 30 and 40. The measured earning/life expectancy are the values that were provided to the treatment group as part of the intervention. For each individual the implied perceived return to high school is computed by taking the difference between the expected earnings upon finishing high school and the expected earnings upon finishing lower secondary. The implied perceived return to university is computed analogously. 3502 students took the survey.

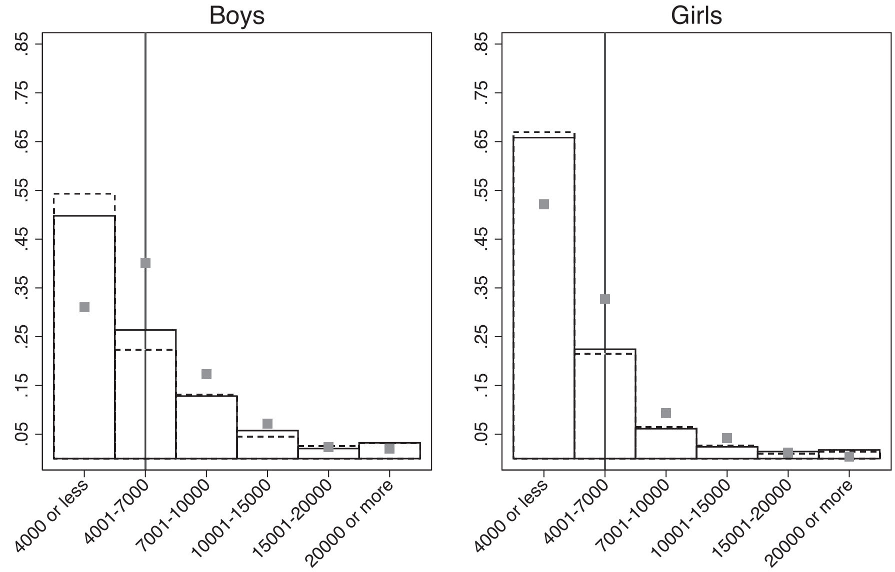


Fig. 2. Baseline Monthly Expected Earnings (Self) upon finishing High School.

ity in subjective valuations of how well oneself can do in the labor market, dispersion in the perceived earning for the average person would just reflect misperception about the average earning. Table 3 reports the gender-specific mean, standard deviation, and coefficient of variation of the expected monthly wages for themselves and for the average person, both upon finishing high school and university. It also reports the mean, the standard deviation, and the coefficient of variation of the implied perceived returns to high school (or university), as defined by the difference between the expected monthly earning upon finishing high school (or university) and lower secondary, and the perceived life expectancy. All the statistics are reported separately for students in the treatment and the control group. In order to assess whether boys and girls are systematically different in terms of beliefs, we test whether the averages for boys and girls in the control group are the same (column 15 in Table 3). For each variable, the observed average is reported and this is the value that students in the treatment group were provided after the survey.

The difference between the treatment and the control group is not statistically significant for any of the elicited beliefs.[19] At the baseline, the average expected monthly wage for oneself, with a high school diploma as the highest degree, as reported both by boys and girls in control schools, is significantly smaller than the real average wage for a man and a woman aged between 30 and 40 with high school degrees. For both sexes, the average expected wage for oneself is 88 percent of the real-world average monthly earning. Girls' coefficients of variation are systematically higher than boys'.

In order to better understand how boys' and girls' beliefs vary, we discretize the baseline answer applying the thresholds used in the follow-up data source, i.e. the 12th grade *ENLACE de contexto*. Fig. 2 plots the distribution of expected earnings (for oneself) at the baseline against the observed distribution in the 2009 ENOE separately for boys and girls. The largest difference between perceived and actual earnings realizations are concentrated in the first two bins of the distribution. In Fig. AII we plot the distribution of the expected earnings for an average person between 30 and 40 and compare it with ENOE.

Both boys' and girls' beliefs about earnings associated with a university degree are on average higher than those observed for a university graduate between 30 and 40 years old, as measured in the ENOE data. This is true irrespective of whether considering the beliefs for oneself or for the average person. This result is consistent with the findings in Hastings et al. (2016) for Chile and Bonilla et al. (2017) for Colombia, with college applicants systematically overestimating the earnings outcomes for past graduates.

Interestingly, when we compute the implied perceived returns for high school—as defined by the difference between the expected monthly earnings for a high school graduate and the expected monthly earnings for a lower secondary graduate—we find that on average they are significantly higher than the actual returns. This suggests that on average students have little knowledge about the salary of a lower secondary graduate, a sum with which that they could potentially have direct experience, and they underestimate it. Whether students base their decisions on the level of earnings or on the earnings' differential between two consecutive levels of education is *a priori* unclear and previous works that explicitly model student choice have followed different approaches.[20] Whether students base their decisions on the earnings or the returns would affect the empirical predictions in our case. If they base their decisions on earnings in levels, since expected average earnings are lower than the true ones, we should observe an increase in the level of effort among students in the treatment group. The opposite would happen if students base their decisions on the expected returns. The last two rows of Table 3 show that both boys and girls tend to overestimate the expected life span, although the size of the misperception is much larger for boys than girls. Unlike for most of the perceived monetary benefits of education, we can not reject the hypothesis that the expected life length is the same for boys and girls.

In summary, we find that students on average underestimate the labor market earnings of high school graduates, but they overestimate those for people with university degrees. Our survey does not elicit student beliefs about the costs of attending university,[21] and whether students know about the existence of financial support. It is therefore

[19] The statistics displayed in Table 3 are generated winsorizing the top 2 percent and the bottom 2 percent of the earnings expectations, but the balancing properties still hold in the untrimmed sample.

[20] Attanasio and Kaufmann (2014) models educational choices as a function of expected returns. Wiswall and Zafar (2015) and Delavande and Zafar (2014) are examples of studies where educational choices are affected by expected earnings.

[21] Hastings et al. (2016) find for Chile that students' beliefs about costs to access higher education are on average correct, although very noisy.

unclear whether the students in our sample overestimate the average monetary net benefit of higher education.

To provide *prima facie* evidence of the link between expected earnings and school performance, Table 4 shows the correlation between the baseline beliefs (expressed in logarithms) and follow-up outcomes for the students in control schools. Although these associations do not have any causal interpretation, it does suggest that expectations of students who are entering high school do bear some relation to the performance in the end of high school national test. Both for the expected earnings and life expectancy we find a small and statistically not significant correlation with the probability of taking the university entry exam EXANI-II.

4. Empirical analysis

4.1. Econometric model

To estimate the causal impact of providing the information package described above, we estimate the following equation:

$$Y_{ij} = \beta_0 + \beta_1 D_j + \gamma' X_{ij} + u_{ij} \tag{2}$$

where Y_{ij} is the outcome of student i in school j recorded in the follow-up data. D_j is an indicator dummy that takes the value one if school j is assigned to the treatment group, 0 otherwise. Since about 16 percent of the evaluation sample did not have access to the computer laboratory, β_1 measures the Intention to Treat (ITT) effect of receiving the information in the modalities explained above. Let X_{ij} be a vector of baseline covariates measured at the individual and school level. In our main specification, X_{ij} includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing. In order to reduce the potential efficiency losses due to the multi-level design of our sampling—at least two classrooms were randomly selected both in treatment and control schools—we follow Cameron and Miller (2015) and in our main specifications we use a Feasible Generalized Least Square (FGLS). OLS results will be displayed in Table AX. In all the specifications, standard errors are clustered at school level to account for correlated shocks within schools, which represent the level at which the treatment is assigned.[22]

Both for math and Spanish, we standardize all the scores using the mean and the standard deviation observed in the control group. In order to address the inference issues related to the presence of multiple learning outcomes (Kling et al., 2007), we also consider the effect on the average test score, as defined by the average of the standardized scores in math and Spanish.

When we study how the treatment effect varies along individual and household characteristics, the results are based on fully interacted models.

4.2. Results on student beliefs

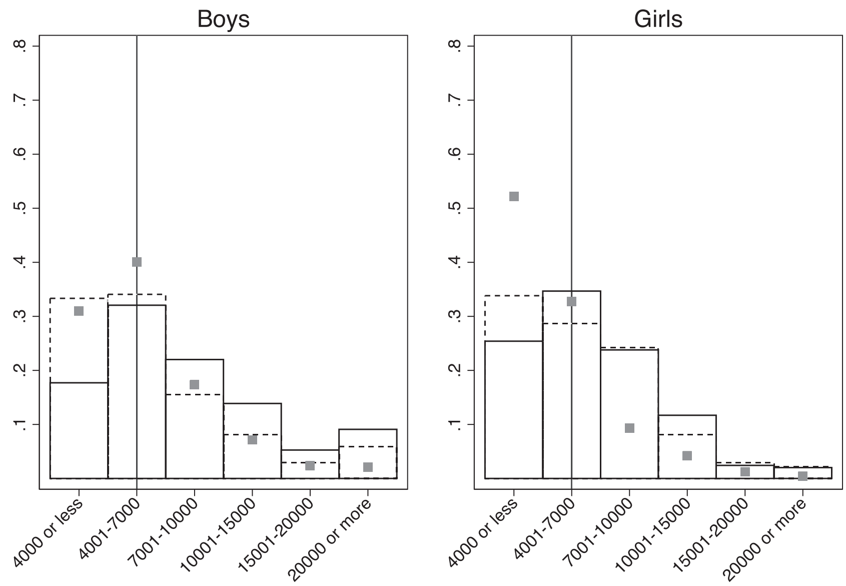
First, we study whether both boys and girls update their beliefs in response to the information treatment. For this purpose, we rely on the administrative information elicited as part of the 12th grade *ENLACE*

Table 4
Correlation between baseline beliefs and student outcomes.

Outcome Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	12th grade ENLACE (Y/N)					12th grade Spanish					12th grade Math					EXANI-II (Y/N)				
(Self) Upper-Sec	0.00					0.14***					0.14***					0.01				
	(0.02)					(0.04)					(0.04)					(0.01)				
(Self) University		0.02					0.15***					0.11***					0.01			
		(0.01)					(0.04)					(0.04)					(0.01)			
(Average) Upper-Sec			0.01					0.09**					0.10**					0.01		
			(0.02)					(0.04)					(0.04)					(0.02)		
(Average) University				0.02					0.09**					0.05					0.01	
				(0.01)					(0.04)					(0.04)					(0.01)	
Life Expectancy					0.12**					−0.08					−0.01					0.05
					(0.06)					(0.17)					(0.16)					(0.05)
N	1438	1438	1438	1438	1438	916	916	916	916	916	916	916	916	916	916	1421	1421	1421	1421	1421
R^2	.0473	.0482	.0474	.0487	.05	.0603	.0628	.0523	.0545	.0484	.105	.102	.0989	.0956	.0934	.0539	.0539	.0539	.0541	.0542

Note: Standard errors in parenthesis. The results are based on an OLS regression restricted to the sample of students in the control group. Additional controls include dummies for the macro-regions where the school is located (north, center and south), dummies for the type of specialization of the school, age and gender of the student, dummies for the presence of a heater, a washing machine, a PC, and internet at home. 12th *grade ENLACE (Y/N)* takes the value 1 if the student took the 12th grade exam in 2012, 0 otherwise. Spanish and Math refer to the 12th grade ENLACE scores in Spanish and math in 2012 and they have been standardized with respect to the mean and the standard deviation. *EXANI-II (Y/N)* takes the value 1 if the student took the EXANI-II either in 2012 or in 2013. (Self) Upper-Sec denotes the log of the expected earnings for oneself between 30 and 40 with an upper secondary degree. (Self) University denotes the log of the expected earnings for oneself between 30 and 40 with a university degree. (Average) Upper-Sec denotes the log of the expected earning for the average person between 30 and 40 with an upper secondary degree. (Average) University denotes the log of the expected earning for the average person between 30 and 40 with a university degree. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

[22] As noticed by Cameron and Miller (2015), if there was within-school cross-classroom correlation of the regressors and errors, then ignoring this correlation (for example, by clustering at the classroom level) would lead to incorrect inference.



Note: The histogram with the solid line plots the beliefs for the Treatment group. The histogram with the dash line plots the beliefs for the Control group. The scatter plots the observed earnings distribution based on data from the ENOE second quarter of 2009. The vertical line is in correspondence with the statistic provided to the students in the treatment group, and it is equal to the average monthly earning for high school graduates aged between 30 and 40 using data from ENOE second quarter of 2009. The baseline expected earnings for themselves upon finishing high school were elicited as part of the baseline survey conducted in November 2009. The follow-up monthly expected earnings for themselves were elicited as part of the 2012 *ENLACE de contexto*, that is administered to 20% of the 12th grade ENLACE exam takers.

Fig. 3. Follow-up Monthly Expected Earnings (Self) upon finishing High School.

de contexto, which asks exam takers about their expected average earnings for high school completion. Two different types of caveats should be taken into account when comparing the expected earnings collected at the baseline and at the follow-up. First, as already mentioned, the *ENLACE de contexto* only collects information among 20 percent of the entire population of exam takers. Given the large share of students who dropped out before taking the 12th grade ENLACE, the populations of exam takers and non-takers might differ along both observable and unobservable characteristics. This has the potential to introduce a selection bias. Due to the randomized assignment of the intervention, the selection bias will not affect the internal validity of our results as long as it enters eq. (2) additively. Nevertheless, the external validity might be limited.

Second, while the question regarding wage expectations included in the 12th grade *ENLACE de contexto* reads exactly as the question included in the baseline survey, the answer only allows the choice between the six options described in section 3.4. In Fig. 3 we plot the distributions of expected earnings in the treatment and the control group both for boys and girls in the follow-up. Compared to the baseline, there is a higher proportion of boys and girls in the control group reporting an expected income in the bin where the observed average earnings fall. Nevertheless, when we test whether the baseline and follow-up distributions for boys and girls in the control group are statistically different, the Pearson χ^2 test does not allow us to reject the null hypothesis that the distributions of expectations have not changed over time.[23]

We observe a reduction in the probability of reporting an expected average monthly wage (for oneself) lower than $4000 MX among boys and girls in the treatment group, compared to those in the control group. Boys in the treatment and the control group do not differ in the probability of reporting an expected average earning between $4000 and $7000 MX, but those in the treatment group are more likely to report expected average earnings in all the bins above $7000 MX. Girls in the treatment group have a larger probability of reporting an expected average monthly wage between $4000 and $7000 MX (where the average true value falls) than girls in the control group. Girls in treatment and control schools do not differ in the probability of reporting expected average earnings above $7000 MX.

The graphical evidence is supported by the regression results presented in Table 5. In the odd columns we present the average effects, while in the even ones we present the gender differentiated ones. In summary, both boys and girls seem to update their beliefs in response to the information received as part of the intervention. However, while girls adjust their perceptions in line with the statistics provided, a significant fraction of boys report values higher than information provided by ENOE. Due to the discrete nature of the data in the follow-up, we can not test whether the program affected the perceived returns.

4.3. Impacts on 12th grade exam

In this section we describe the results of our experiment on four main education outcomes at the end of high school: the probability of taking the 12th grade ENLACE on time—i.e. three years after the start of high school, standardized Spanish test score, standardized math test score and the average of the two. In Table 6 we present the ITT effects for the whole sample. In the odd columns we present the results for the specification that does not control for the 9th grade level of knowledge in math and Spanish. In the even columns we present the results based on the main specification described in section 4.1.

[23] The p-values are 0.286 and 0.597 for boys and girls respectively. However, due to the limited number of observations, this result should be interpreted cautiously.

Table 5
Effect on perceived earnings.

	(1) Less than 4000	(2)	(3) Between 4000 and 7000	(4)	(5) Above 7000	(6)
Treatment	−0.139***		0.050**		0.084**	
	(0.048)		(0.020)		(0.041)	
Treat X Male		−0.174***		0.003		0.163***
		(0.046)		(0.028)		(0.050)
Treat X Female		−0.116**		0.089***		0.025
		(0.058)		(0.026)		(0.044)
Strata Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	728	728	728	728	728	728
Mean Dep. Control Group	0.336	0.336	0.314	0.314	0.351	0.351
SD Dep. Control Group	0.473	0.473	0.465	0.465	0.478	0.478
P Value $H_0: Boys = Girls$		0.134		0.024		0.002

Note: Robust standard errors clustered at school level in parentheses. The full set of controls includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing. The dummy *Less than $4000 MX* takes the value 1 for an expected monthly earning below $4000 MX upon finishing high school, 0 otherwise. The dummy *Between $4000 MX and $7000 MX* takes the value 1 for an expected monthly earning between $4000 MX and $7000 MX upon finishing high school, 0 otherwise. The dummy *More than $7000 MX* takes the value 1 for an expected earning above $7000 MX upon finishing high school, 0 otherwise. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

In our baseline specification, we find that in the treatment group the probability of taking the exam increases by one percentage point, but the effect is not statistically significant. We interpret this result as evidence that the intervention did not affect on-time high school completion.

We next consider the effect on students' learning outcomes. The results are presented in columns 3 to 8 in Table 6. The treatment effect is equal to 0.16σ and not statistically significant for Spanish and 0.33σ and significant for math when we dot not control for student level of preparadness. For the average of the two scores, we find an effect of 0.24σ, statistically significant at a 10 percent level. When we include the full set of baseline controls, the effect of the information treatment is equal to 0.14σ (not statistically significant) for Spanish, 0.31σ for math (significant at 5 percent) and 0.23σ (significant at 5 percent) for the average score. The treatment effects on learning outcomes are sizeable even when they are compared to the estimated coefficients for other characteristics. For instance, boys score on average 0.30σ higher than girls in math. Since students can report their household income only opting for pre-specified brackets, we define as "high HH income" those students who report a monthly household income in the bracket between $3501 and $7000 MX or higher, while those who report an income in a lower bracket are classified as "low HH

Table 6
Impact on high school performance.

Outcome Variable	(1) ENLACE (Y/N)	(2)	(3) Spanish	(4)	(5) Math	(6)	(7) Average Score	(8)
Treatment	0.029	0.010	0.160	0.139	0.326**	0.308**	0.244*	0.225**
	(0.036)	(0.030)	(0.125)	(0.106)	(0.154)	(0.144)	(0.128)	(0.112)
Male	−0.062***	−0.050***	−0.034	0.001	0.336***	0.341***	0.153***	0.174***
	(0.017)	(0.016)	(0.038)	(0.038)	(0.037)	(0.036)	(0.032)	(0.030)
High HH Income	0.006	0.003	0.145***	0.114***	0.089***	0.068**	0.115***	0.090***
	(0.013)	(0.013)	(0.040)	(0.039)	(0.034)	(0.033)	(0.032)	(0.032)
Suff. Math Readiness		0.132***		0.408***		0.496***		0.448***
		(0.023)		(0.043)		(0.044)		(0.036)
Suff. Spanish Readiness		0.080***		0.563***		0.217***		0.387***
		(0.023)		(0.060)		(0.052)		(0.051)
Strata Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4145	4145	2531	2531	2531	2531	2531	2531
Mean Dep. Control Group	0.598	0.598	0.000	0.000	0.000	0.000	0.000	0.000
SD Dep. Control Group	0.490	0.490	1.000	1.000	1.000	1.000	0.884	0.884

Note: Robust standard errors clustered at school level in parentheses. The full set of controls (both displayed and not displayed) includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing. *ENLACE (Y/N)* takes the value 1 if the student took the 12th grade exam in 2012, 0 otherwise. *Spanish* and *Math* refer to the 12 grade ENLACE scores in Spanish and math in 2012 and they have been normalized with respect to the mean and the standard deviation in the control group. The *Average Score* is the average of the normalized scores in Spanish and math. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

income".[24] Belonging to a household with a monthly income higher than \$3500 MX is associated with an increase of 0.11σ in Spanish, and 0.07σ in math. As discussed above, the level of proficiency in lower secondary, as measured by the 9th grade ENLACE, is a strong predictor of the probability of completing high school. Based on their ENLACE results, students are classified in one of the following proficiency levels: (a) insufficient, (b) regular, (c) good, and (d) excellent. We define as sufficient-readiness students those who score regular or higher in the 9th grade ENLACE, and as low-readiness students those who score insufficient.[25] For students who scored at least regular in the 9th grade math ENLACE exam, the 12th grade ENLACE math and Spanish scores are 0.50σ and 0.41σ higher than for those who displayed low readiness.

Since we found no impact of the intervention on the probability of taking the ENLACE exam, it is unlikely that the effect on test scores is driven by differential selection into the ENLACE exam in treatment and control schools. If anything, any positive effect on the probability of taking the exam should lead to a downward biased estimate of the treatment effect on the scores in math and Spanish. In fact, consistent with the evidence presented in Dustan et al. (2017), when we restrict the sample to students in control schools we find that the probability of taking the ENLACE exam in 2012 is positively and strongly correlated with student academic ability, as proxied by the 9th grade ENLACE scores (see Table AV). Therefore, the marginal students - defined as those who would have not taken the exam in the absence of the intervention - would be academically weaker than the average ones. We check whether, as a result of the selection, the exam takers in the treatment group differ from those in the control group, but we find no evidence of imbalances either in the full sample or in the restricted samples of boys and girls (see Table AVI).

We perform a variety of robustness tests. Rather than controlling for the levels of proficiency in the 9th grade ENLACE exam, we include the standardized 9th grade scores. The results, not presented, are basically identical to those in Table 6. In order to assess whether the effects on student learning persist once we account for repetition, we test whether the intervention had an impact on the probability of taking the 12th grade ENLACE either in 2012 or in 2013, and on the scores in either exam. Results presented in AVII are in line with those presented in Table 6. While less precise, the OLS estimates for high school outcomes (columns 1–4 in Panel A in Table AX) are consistent with the main results. Results in columns 1–4 in Panel B in Table AX show that the results are almost unchanged when we restrict the sample to those who had access to the computer lab.

In this section, we documented that *Percepciones* had no impact on the proxy for completing high school on-time, but had a fairly large and statistically significant effect on test scores. The average effect size on student test scores is in line with the one found by Nguyen (2008) when studying the short term impact of a similar information treatment targeting parents and children in Madagascar primary schools, and not statistically different from the one found by Fryer (2016a) when studying the medium term effects of a US based intervention that provides information on human capital returns through text messages. Our results show that also in a developing country context information interventions can affect learning outcomes in the medium term, and most importantly, at a stage of academic life that is crucial for future entry into academia and labor markets. The reduced form estimates presented in this section have to be interpreted as the cumulative effect of adjusting the perceptions about earnings for high school and university completion, funding opportunities for university, and life expectancy.

[24] In 2012, the median price adjusted household income was \$4880 MX.

[25] In our sample about 16 percent and 30 percent of the students in our sample taking the 9th grade ENLACE were classified as insufficient in Spanish and math respectively.

4.4. *Treatment heterogeneity in high school performance*

We next consider how the treatment effect varies with three important dimensions: gender, academic readiness and household income. The experiment was not designed to be representative at any of these levels. Therefore our results have to be interpreted as suggestive, rather than conclusive.

The intervention provided both boys and girls with gender specific measures of the returns to human capital investment and its potential time horizon. We study whether boys and girls responded differentially to the information provision. Results are presented in Panel A in Table 7. In the control group, girls are more likely to take the test than boys (63 percent vs 57 percent). Nevertheless, the effect of the information treatment on the probability of taking ENLACE 12th grade on time is basically null for both boys and girls. When we look at the impact of the information treatment on learning outcomes, for boys we find no effect on Spanish test scores, but a sizeable and marginally significant increase in math scores (0.24σ). For girls we find a moderate positive effect on scores in Spanish (0.16σ marginally significant at 10 percent level) and a large (0.34σ) and statistically significant impact on math scores. These impacts translate into a 0.25σ (statistically significant at 5 percent level) increase in the average score for girls, and a 0.15σ non-statistically significant increase for boys. We can marginally reject the null hypothesis of no gender-differentiated effect on the average learning score (p-value = 0.051).

We start exploring whether the intervention interacted with student initial condition, by allowing the treatment effect to vary with the level of readiness in math, as proxied by the results in the 9th grade ENLACE. Results are reported in Panel B in Table 7. The main conclusions are virtually the same when we interact the treatment with the level of readiness in Spanish (not displayed). The effect on the proxy for finishing high school on time is not statistically different from zero, irrespective of the level of math readiness. When we look at learning outcomes, we find that among low-readiness students, the effect is 0.05σ for Spanish and 0.25σ for math. For both subjects, as well as for the average test score (column 4) the effect is not statistically different from zero. For those with an ENLACE proficiency level of regular or more, we find a large effect both on Spanish and math, 0.15σ and 0.33σ respectively, with the effect on the average test score (0.24σ) being statistically significant at 5 percent level. Nevertheless we cannot reject the hypothesis that the effect for the low-readiness students is the same as for sufficient-readiness ones. In summary, although we find larger coefficients for students with sufficient level of preparedness, we do not have enough statistical power to rule out the null hypothesis of no differential effect.

We repeat a similar exercise using household income. Results in Panel C in Table 7 show how the treatment effects vary with the dummies that proxy for different levels of household income. Income does not affect the program's effect on the probability of taking the 12th grade ENLACE exam. The treatment effects on learning outcomes among low income students are not statistically different from zero, although the size of the effect is nontrivial for the math score (0.20σ). Among relatively high income students the effect is positive and marginally significant on Spanish (0.18σ) and large for math (0.32σ). When we consider the effect on the average learning score, we find a 0.12σ increase among low income students, as opposed to a 0.25σ (statistically significant at 5 percent) among high-income students, and a 0.17σ increase among students who did not report income. We can reject the null hypothesis of no differential effect between low and high income students (p-value = 0.028), while we can not reject it when we compare low income students with those who do not report income information. There is no evidence that the treatment heterogeneity is driven by imbalances in the baseline characteristics across the three income groups of students (Table AVIII).

Table 7
Treatment heterogeneity.

Outcome Variable	(1) ENLACE (Y/N)	(2) Spanish	(3) Math	(4) Average Score
Panel A Heterogeneity by Gender				
Treatment X Male	−0.001	0.063	0.237*	0.152
	(0.032)	(0.106)	(0.139)	(0.108)
Treatment X Female	0.009	0.162*	0.338**	0.253**
	(0.034)	(0.094)	(0.144)	(0.104)
Strata Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	4131	2520	2520	2520
P-Value H_0: Boys = Girls	0.722	0.128	0.102	0.051
Panel B Heterogeneity by Math Readiness				
Treatment X Low Readiness	−0.017	0.041	0.247	0.148
	(0.043)	(0.117)	(0.169)	(0.127)
Treatment X Suff. Readiness	0.025	0.152	0.333***	0.242**
	(0.027)	(0.098)	(0.129)	(0.101)
Treatment X Missing Readiness	0.004	0.113	0.348*	0.235
	(0.045)	(0.180)	(0.187)	(0.166)
Strata Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	4131	2520	2520	2520
P-Value H_0: Low Readiness = Suff. Readiness	0.248	0.167	0.312	0.182
P-Value H_0: Low Readiness = Missing Readiness	0.658	0.596	0.355	0.450
Panel C Heterogeneity by HH Income				
Treatment X Low Income	0.011	0.047	0.198	0.124
	(0.035)	(0.098)	(0.148)	(0.107)
Treatment X High Income	−0.005	0.178*	0.322**	0.254**
	(0.029)	(0.104)	(0.135)	(0.105)
Treatment X Missing Income	0.019	−0.037	0.379**	0.174
	(0.043)	(0.131)	(0.184)	(0.144)
Strata Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	4131	2520	2520	2520
P-Value H_0: Low Income = High Income	0.493	0.065	0.060	0.028
P-Value H_0: Low Income = Missing	0.859	0.428	0.143	0.628

Note: Robust standard errors clustered at school level in parentheses. The full set of controls includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

The evidence on the treatment heterogeneity with respect to academic preparedness and parental income suggests that the intervention has a stronger effect on students who have better initial conditions. This can help explain the lack of significant impact on the probability of completing on time. The risk of dropping out of high school is highest among students who have the worst initial conditions, who are indeed less likely to benefit from our intervention. In section 5, we will provide some evidence on some of the possible behavioral changes behind such a large treatment heterogeneity.

4.5. Impacts on university entry exam

In this section we provide evidence on the average impact of the intervention on the probability of taking the university entry exam EXANI-II either in year 2012 or 2013, and on the probability of scoring 1150 points or above in the test, that would correspond to an outstanding level.

The results are displayed in Table 8. We present results both without (odd columns) and with (even columns) controls for the level of proficiency in 9th grade math and Spanish ENLACE tests. In our main specification (column 2), we find that *Percepciones* led to an increase in the probability of taking the EXANI-II test by 3.9 percentage points. Although the effect is statistically not significant, the size is not trivial as it corresponds to about 0.10σ. Since the test is not a requirement for students who enroll into private universities and a non-negligible share of public universities, we expect our treatment effect to be a lower bound estimate of the true impact of *Percepciones* on university enrollment. The discussion in section 3.1 can help us make sense of the positive impact on university enrollment. The group of students who underestimate both the earnings associated with upper secondary and university education, for whom our model predicted an unambiguously positive effect, represents by far the largest share (55 percent), followed by those who overestimate the earnings associated to both school levels

Table 8
Impact on university entry test.

Outcome Variable	(1) EXANI-II (Y/N)	(2)	(3) EXANI-II above 1150 (Y/N)	(4)
Treatment	0.050	0.039	0.025	0.022
	(0.042)	(0.039)	(0.029)	(0.027)
Male	0.028*	0.036**	0.053**	0.061***
	(0.016)	(0.016)	(0.023)	(0.022)
High HH Income	0.011	0.010	0.026	0.019
	(0.016)	(0.016)	(0.026)	(0.025)
Suff. Math Readiness		0.086***		0.103***
		(0.022)		(0.019)
Suff. Spanish Readiness		0.064***		0.035***
Strata Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	4090	4090	898	898
Mean Dep. Control Group	0.246	0.246	0.071	0.071
SD Dep. Control Group	0.431	0.431	0.257	0.257

Note: Robust standard errors clustered at school level in parentheses. The full set of controls (both displayed and not displayed) includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above \$3500 MX, and a dummy for whether the information on household income is missing. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. *EXANI-II (Y/N)* takes the value 1 if the student took the EXANI-II either in 2012 or 2013, 0 otherwise. *EXANI-II above 1150* takes the value 1 if the score was above 1,150, 0 otherwise.

(24 percent).[26]

In principle, we could expect that as the share of high school graduates who take EXANI-II increases, academically weak students are more likely to take the test. Nevertheless, when we look at the impact of *Percepciones* on the probability of being classified as outstanding in the exam, we find that the treatment effect is positive, although not statistically significant. We interpret this result as evidence that *Percepciones* led to an average improvement in university readiness.

Also for university outcomes, the results are unchanged when we estimate OLS specifications, and we restrict the sample to those who had access to the computer lab (columns 5 and 6 in Panels A and B in Table AX). Overall, although the treatment effects are not statistically significant, the results discussed in this section support the conclusion that *Percepciones* improved outcomes that are of particular relevance for individual labor market outcomes.

5. Potential mechanisms

5.1. Impact on student effort

In the simple theoretical framework outlined in section 3.1, information improves students' performance through an increase in the level of effort. While objective measures of effort are not available, we use the self-reported measure of effort elicited in the 12th grade *ENLACE de contexto* (described in appendix B.2) to assess whether the intervention induced students to work harder. In the control group, 26 percent of the boys, as opposed to 18 percent of the girls, report that the statement “I am a person who works hard in school” describes them fully, while for 24 percent of the boys and 23 percent of the girls say the statement describes them a lot.

The major concern when using self-reported measures in a context like ours is the possibility of *social desirability* bias: students in the treatment group might be more likely to reply in a way that others would view favorably. The measure of self-reported effort that we use was collected almost three years after the intervention as part of a standard nationally administered survey, and it is therefore unlikely that students could bias their response as a result of the information treatment. Previous work (Stinebrickner and Stinebrickner, 2004) has found that self-reported measures of study effort are affected by substantial measurement error. In order to boost confidence in our measure, we use data from the control group to measure the correlation between the self-reported level of effort and the 2012 ENLACE results in math and Spanish. One standard deviation increase in self-reported effort leads to a 0.11σ increase in math and 0.12σ in Spanish, and both correlations are statistically significant at conventional levels.

We use eq. (2) to analyze the impact of the information treatment on self-reported levels of effort. In order to simplify the interpretation of the results, we standardize the categorical variable using the mean and the standard deviation observed in the control group. Results are presented in Table 9. Column 1 shows the results for the entire sample. Overall the treatment group reports a level of effort that is 0.24σ (statistically significant at 1 percent level) higher than for the control group. In column 2, we consider the effect by gender and we find much larger impact for girls (0.35σ) than for boys (0.11σ). We can marginally reject the null hypothesis of no differential effect by gender (p-value = 0.07). In columns 3 and 4 we present how the effect of *Percepciones* on self-reported effort varies with the level of school readiness and household income respectively. We do find evidence of increases in effort for all the different subgroups but neither for readiness nor for household income there is evidence of treatment heterogeneity. This result is consistent with the fact that we find little evidence that the beliefs of students with high and low initial conditions responded differentially to the treatment (Table AIX).

In section 3.4 we discussed how in our context the predictions about the impact on student effort would change depending on whether students base their decisions on the expected earnings or on expected returns. The positive impact on self-reported effort documented in this section is consistent with the former hypothesis. We also find that the effect is larger for those who reported baseline expected

[26] The students who underestimate the average earnings for upper secondary and overestimate those for university represent 16 percent, with 5 percent of the students doing the the opposite.

Table 9
Impact on self-reported effort.

	(1) Full Sample	(2) Gender	(3) Math Readiness	(4) HH Income
Treatment	0.240***			
	(0.027)			
Treatment X Male		0.110		
		(0.094)		
Treatment X Female		0.349***		
		(0.060)		
Treatment X Low Readiness			0.297 ***	
			(0.080)	
Treatment X Suff. Readiness			0.156*	
			(0.082)	
Treatment X Missing Readiness			0.194	
			(0.161)	
Treatment X Low Income				0.222 ***
				(0.078)
Treatment X High Income				0.303 ***
				(0.071)
Treatment X Missing Income				0.054
				(0.174)
Strata Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	724	724	724	724
Mean Dep. Control Group	−0.000			
SD Dep. Control Group	1.000			
P-Value H_0: Boys = Girls		0.071		
P-Value H_0: Low Readiness = Suff. Readiness			0.359	
P-Value H_0: Low Readiness = Missing Readiness			0.526	
P-Value H_0: Low Income = High Income				0.477
P-Value H_0: Low Income = Missing				0.320

Note: Robust standard errors clustered at school level in parentheses. The full set of controls includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing. The self-reported effort has been standardized with respect to the mean and the standard deviation in the control group. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

earnings below the observed average (0.20σ, statistically significant at 5 percent) than for those who reported expected earnings above (0.13σ), but we can not reject the null hypothesis of no differential treatment.

Although the self-reported nature of the data requires a cautious interpretation of the results presented in this section, the gender-differentiated effect on learning outcomes documented in section 4.3 can be potentially explained by the differential treatment effect on effort. The information intervention seems to have improved students' intrinsic motivation, irrespective of their level of school preparedness and household income. The fact that learning outcomes only increase among high-income students, although both high- and low-income students report higher self-reported effort, is consistent with the hypothesis of complementarity between student effort and other inputs in the learning production function (Cunha and Heckman, 2007). This result further supports the hypothesis that the lack of significant impact on on-time completion can be explained by the fact that students who are at risk of dropping out do not have the minimal preconditions to benefit from the intervention. An alternative explanation is that only students from relatively well-off backgrounds know how to translate increased effort into better outcomes.

5.2. Evidence on the gender heterogeneity

In this section we first study whether additional objective measures support the conclusions based on the self-reported measures of effort, and we then test some of the potential mechanisms behind the gender-differentiated responses.

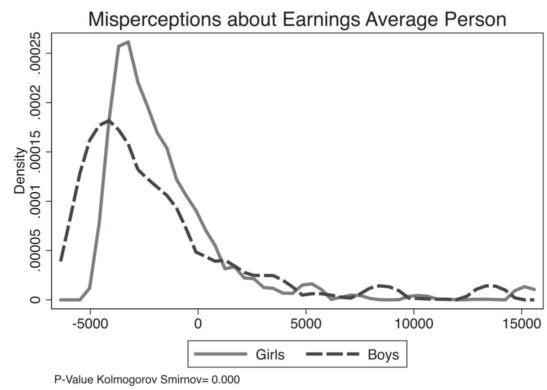
Recent studies for the US (Goldin et al., 2006; Fortin et al., 2015) have shown that one of the reasons why women have overtaken men in high school performance and college attainment over the last decades is that changes in the returns to different professions have caused more women to shift from vocational to more academic courses. In our sample, students can potentially choose different subtracks, which broadly differ in the level of math intensity.[27] The subtrack of physics and mathematics offers the widest choice of math related courses, followed by the economics and accounting, and chemistry and biology. We compare the school subtrack distribution of students in the treatment and for boys and girls in treatment and control schools. Results are reported in Table 10. Among boys we do not find any significant difference in the subtrack distribution between treatment and control groups; a vast majority of students prefer the physics and mathematics subtrack (48 percent) followed by economics (20 percent) and chemistry (13 percent). For girls, the percentage who prefer physics and mathematics is 27 percent, not statistically different in the treatment and the control group. But we do find a much larger fraction of girls taking economics courses in the treatment groups (35 percent) vis-a-vis the control group (19 percent), with a consequential reduction in the uptake of chemistry

[27] Each subtrack has a large set of optional courses and students have to choose two of them for a total of ten weekly hours during the last semester of high school.

Table 10
Subtrack distribution.

	(1) Boys	(2)	(3)	(4) Girls	(5)	(6)
	Control	Treatment	Total	Control	Treatment	Total
None	21.64%	17.87%	19.35%	20.90%	22.22%	21.75%
Physics and Mathematics	48.51%	47.83%	48.09%	29.10%	25.51%	26.79%
Chemistry and Biology	13.43%	12.08%	12.61%	31.34%	16.87%	22.02%
Economics and Administrat.	16.42%	22.22%	19.94%	18.66%	35.39%	29.44%
N	134	207	341	134	243	377
	Pearson $\chi^2(3) = 2.08$		p-value = 0.552	Pearson $\chi^2(3) = 16.92$		p-value = 0.001

Note: The bottom line reports the chi-square test, and the p-value for the null hypothesis of equality of distributions.



Note: The graph plots the distribution of the variable constructed by taking the difference between the expected earnings for an average person between age 30 and 40 with upper secondary and observed average earnings, based on the information collected at the baseline.

Fig. 4. Misinformation about the monetary benefits of upper secondary at the baseline.

and biology. A Pearson χ^2 test allows us to reject the null hypothesis that the subtrack distribution is the same in the treatment and control group for girls, but we cannot reject the null hypothesis for boys. The improvement in the math scores of girls in the treatment group might be related to girls choosing subtracks with higher intensity of the math instruction.

For this result, there is a possible explanation that the available data did not allow us to test: our intervention motivated female students to search for more detailed information about the wages related to different careers. It is possible that female students in the treatment group use Mexico's nationwide employment observatory (*Observatorio Laboral* - OLA) which can be easily accessed through a webpage and since 2005 has provided updated gender-specific information on the main labor market outcomes of the different high school tracks.[28]

As discussed in section 3.2, at the baseline proxies for student effort were on average the same for boys and girls. It is puzzling that in response to the information provision both boys and girls update upwards their perceptions regarding the monetary benefits of finishing EMS, but only girls report higher effort and higher test scores in 12th grade. We next discuss whether the gender differential treatment effect can be explained by differences along four possible dimensions: 1) self-reporting, 2) extent of the misperceptions at the baseline, 3) information content, 4) characteristics that can potentially drive heterogeneous responses.

The lack of effect on self-reported measures of effort might by explained by the presence of reference bias, which occurs when individual responses are influenced by differing implicit standards of comparison. If this bias differs for boys and girls, this can potentially explain why we only find an effect on girls' effort. We can not rule out this explanation for the perception about being a hard worker (Table 9), but this is much less likely to apply when studying the effect on subtrack choice (Table 10).

Although on average both boys and girls reported beliefs about the earnings associated with upper secondary completion lower than the actual ones, the extent of the misinformation might differ. In order to assess this possibility, we construct a continuous measure of misinformation by taking the difference between the expected earning for an average person aged between 30 and 40 elicited in the survey and the observed value. The distribution both for boys and girls is plotted in Fig. 4. Using a Kolmogorov-Smirnov test, we can reject the null hypothesis that boys' and girls' distribution are the same. But there is no clear evidence that girls are more misinformed than boys, as this would in principle lead to a larger impact in effort for the former compared to the latter. However, we can not rule out that boys are less likely to increase effort than girls because at the baseline they were over optimistic about their life expectancy.

The information content is different for boys and girls, because the monetary benefits associated with different education levels are different. Our data do not allow to separate to what extent the gender-differentiated effect on effort and learning is driven by differences in the information content and in characteristics that can lead to het-

[28] According to the public information provided by the OLA in 2014, a nurse, one of the most common professional outcomes for students choosing the chemistry and biology subtrack, receives on average $8617 MX per month and 87 percent of the nurses are female. The average wage for a clerk is $10,215 MX and $10,212 MX for an accountant, two common outcomes for those opting for an economics and administration subtrack. Among clerks and accountants, women account for 49.3 percent and 46.4 percent of the total employees respectively. Careers such as engineering, that are common outcomes for those taking the physics and mathematics subtrack have on average the highest wages but an extremely low proportion of women. For example, the average wages for a mining engineer is $19,838 MX, but the percentage of women among the profession's members is 11.4 percent. For automotive engineers, the average pay is $14,036 MX per month, but there is only a 1.3 percent share of women.

Table 11
Understanding gender differences: The role of time preferences.

	(1) Self-Reported Effort Full Sample	(2) Average Score Full Sample
Treatment X Low Discount	0.301***	0.233**
	(0.041)	(0.115)
Treatment X High Discount	−0.071	0.148
	(0.144)	(0.122)
Strata Dummies	Yes	Yes
Controls	Yes	Yes
N	715	2511
P-Value H_0: Low Discount = High Discount	0.011	0.226
Proportion of boys with Low Discount	0.805	0.805
Proportion of girls with Low Discount	0.852	0.852

Note: Robust standard errors clustered at school level in parentheses. The full set of controls includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing, and the time discount dummies. The dummy *Low Time Discount* takes the value 1 if the respondent would be willing to renounce $3000 MX today in order to receive a higher amount in the future, 0 otherwise. The dummy *High Time Discount* is defined as the opposite of *Low Time Discount*. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

erogenous responses. We investigate some of the potential sources of response heterogeneity based on the insights from previous work on gender differences. In the baseline survey we elicited information on time preference using a framework similar to the one used by Rubalcava et al. (2009) and described in section 3.2. Consistent with their results and other recent studies (Dittrich and Leipold, 2014; Bauer et al., 2012), we find that women have lower time discount than men: 20 percent of boys, as opposed to 15 percent of girls, would prefer accepting $3000 MX today, regardless of a higher amount offered in one year's time. We define these individuals as the "high time discount" students, while we define as "low time discount" all students willing to forego the $3000 MX today in exchange for a larger sum in the future. Lower time discount should lead to an increased impact of the information package on student effort. The data presented in column 1 in Table 11 show that low time discount students in the treatment group display a very large and statistically significant response in self-reported effort, as opposed to a zero impact among the high discount students. Point estimates on the average learning score show larger coefficients for low time discount than high discount students (column 2 in Table 11), but we can not reject the null hypothesis of no differential effect. Given the small difference in the proportion of high discount students among boys and girls, and the fact that we can not reject the hypothesis that the effect on learning is the same for high and low time discount students, we conclude that the role of time preferences in explaining the gender-differentiated effect on learning is at most small.

Table 12
Additional explanations for the gender-differentiated effects.

Outcome Variable	(1) Math Teacher solves doubts	(2) Math Teacher gives exercises	(3) Math Teacher involves students	(4) Parents monitor attendance	(5) Parents monitor grades	(6) Parents monitor homework	(7) Never married	(8) Aspirationsv score
Treat X Male	−0.007	0.037	0.040	−0.039	0.004	−0.076*	−0.016	0.045
	(0.042)	(0.041)	(0.042)	(0.038)	(0.044)	(0.039)	(0.016)	(0.145)
Treat X Female	0.006	−0.079	−0.055	−0.023	−0.061*	−0.083**	0.049**	0.407*
	(0.047)	(0.064)	(0.071)	(0.019)	(0.037)	(0.036)	(0.021)	(0.231)
Strata Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	729	729	727	730	730	729	727	730
P-Value H_0: Female = Male	0.723	0.146	0.257	0.673	0.208	0.899	0.010	0.092
Mean Dep. Control Group	0.853	0.707	0.338	0.762	0.846	0.581	0.960	0.000
SD Dep. Control Group	0.355	0.456	0.474	0.427	0.361	0.494	0.197	1.000

Note: Robust standard errors clustered at school level in parentheses. The full set of controls includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing. The dummy *Math Teacher gives exercises* takes the value 1 if the student reports that the math teacher gives exercises to assess her/his comprehension, 0 otherwise. The dummy *Math Teacher involves students* takes the value 1 if the student reports that the math teacher involves students during the class, 0 otherwise. The dummies *Parents monitor attendance*, *Parents monitor grades*, *Parents monitor homeworks* take the value 1 if students report their parents monitor attendance, grades, homework respectively, 0 otherwise. The dummy *Never married* takes the value 1 if the student is single, 0 if he/she is either married or divorced/separated. The educational *Aspirations score* has been generated by standardizing the categorical variable described in section 3.3 with respect to the mean and the standard deviation in the control group. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Information about future returns to children's education might in principle affect parental expectations and, as a result, their investments into their children's human capital.[29] Parents might invest more in girls if they discovered they were underestimating their future labor market returns.[30] Although teachers in treatment schools were not exposed to the information, they might have increased their effort, possibly as a result of a Hawthorne effect, but it is unclear why this would have a differential effect on boys and girls. We test whether the intervention led to teachers' and parents' responses that differ with student gender. In the *ENLACE de contexto* students are asked a series of questions about their math teachers' practices and parental investment. Evidence presented in columns 1 to 6 in Table 12 shows no gender-differentiated effect of the program on students' perceptions about teacher practices and parental involvement. If anything, parents to female students in the treatment group reduce the propensity to supervise, possibly as a result of their daughters' increased effort.

Previous work for Mexico has shown that girls' expectations and aspirations regarding the quality of the potential partner and family formation are predominant in their schooling decisions (Attanasio and Kaufmann, 2012a), and this might explain why they stay away from the most math-intensive subtracks. One hypothesis is that the *Percepciones* intervention changed girls' aspirations.[31] In order to provide some evidence for this hypothesis, we use the information on the marital status and education aspirations elicited in the *ENLACE de contexto*. We define the variable *Never Married* as a dummy that takes the value 1 if the student reports being single, and 0 if he/she is currently married or divorced/separated. In order to measure the impact on educational aspirations, we standardize the categorical variable using the mean and the standard deviation observed in the control group. The results are presented in columns 7 and 8 in Table 12. In the control group, 98 percent of the boys as opposed to 94 percent of the girls reported being single. *Percepciones* did not affect the probability of being single among boys, but it increased it for girls by 4.5 percentage points (column 7).[32] The intervention did not affect boys' aspirations, but it had a positive and statistically significant impact on girls' aspirations (0.37σ).

Due to the small sample for which the *ENLACE de contexto* is available and the fact the evaluation was not designed to separately identify the effects on boys and girls, we must interpret the results presented in this section as suggestive, rather than conclusive. We do find support for the hypothesis that girls, unlike boys, responded to the information treatment by increasing the level of effort. Differences in time preferences and responses of parents and teachers do not seem to be important in explaining the gender-differentiated response. There is evidence that the information package might have induced girls to increase their education aspirations and give more salience to labor market considerations, rather than those related to family formation, when deciding the amount and type of effort in school. The results in this section are consistent with the hypothesis that *Percepciones* generated a 'snowball effect', especially among girls, and the impact on student performance reflects the cumulative effect of student behavioral changes.

6. Conclusions

When entering high school, students face important decisions that can have long-lasting consequences on their education and labor market trajectories. Often these decisions are taken without an adequate level of information, especially in developing countries. This paper studies whether a purely informational intervention can have medium-term effects on students' performance at the end of high school. We analyze the impact of an intervention that targets 10th grade students in Mexico and provides them information about the (1) earnings associated with high school and university education, (2) a program that they might tap for financial aid for tertiary education, and (3) life expectancy. The *Percepciones* pilot displayed no impact on the probability of on-time high school graduation, but had a large positive effect on learning outcomes and a more modest effect on a university entry exam. We find evidence of strong complementarity between the intervention and students' initial conditions, which could at least partly explain why the intervention improved test scores but not on-time graduation.

Girls who received the intervention report higher levels of effort and achieved a larger increase in test scores than boys. Although our study was not designed to analyze a differential impact based on gender, the available data do allow us to test whether some of the mechanisms previously mentioned by the literature can operate in our context. We find support to the hypothesis that the information package changed girls' aspirations because they were less likely to have been married and they aim to complete higher levels of education.

The results presented in this paper show that a pure informational treatment is not an effective strategy to reduce high school dropout rates, at least in contexts where the effort required to complete high school on time is high. While our results confirm that, on average, information interventions are a cost-effective way to increase student effort, they can potentially exacerbate existing socioeconomic inequalities. Students from disadvantaged backgrounds are less likely to be able to improve their learning outcomes, because the increase in effort needs other inputs.

A. Description of the survey and intervention

A.1. Questions to elicit expected earnings

Using the same questions administered during the *Jóvenes con Oportunidades con Oportunidades* survey, the interface asked three questions about individual own expected earnings:

[29] Dizon-Ross (2017) shows for Malawi that parents' inaccurate beliefs about their children's academic ability cause the misallocation of education investments. Boneva and Rauh (2018) use data from the UK to show that that parental beliefs about the returns to investments vary substantially across the population and that individual beliefs are predictive of actual investment decisions.

[30] Bharadwaj et al. (2012), using data from Chile, find that parents invest more in math for boys, while the reverse is true for reading.

[31] Oreopoulos and Dunn (2013) when studying the impact of an intervention that provides high school students from low income families with online information about costs and benefits of post secondary education, finds a statistically significant increase in student aspirations.

[32] In alternative specifications we estimate the impact on the probability of being never married and educational aspirations using a probit and an ordered logit model (using the categorical variable) respectively. The conclusions are perfectly in line with those presented in this paper.

1. If you were to quit studying right now and therefore lower secondary was your highest degree, what do you think is the amount you could earn per month at ages 30 to 40?
2. If you finish high school and do not continue studying, what do you think is the amount you could earn per month at ages 30 to 40?
3. If you get a university degree and do not continue studying, what do you think is the amount you could earn per month at ages 30 to 40?

Individuals were also asked about the expected earnings for an average persons:

1. What do you think is the amount earned per month by a man (woman) between 30 and 40 years old with a lower secondary degree?
2. What do you think is the amount earned per month by a man (woman) between 30 and 40 years old with a high school degree?
3. What do you think is the amount earned per month by a man (woman) between 30 and 40 years old with a university degree?

A.2. Information about earnings

> In Mexico a man (woman) between 30 and 40 years old with a maximum education level of lower secondary earns, on average, $4,832 ($3,179) MX per month.[33] A man (woman), ages 30 to 40, with a high school diploma earns, on average, $6,466 ($4,827) MX per month, or $1,634 ($1,648) MX more per month. Therefore a man (woman) with a high school diploma earns, on average, $784,320 ($791,040) MX more than a person with a lower secondary degree throughout his (her) productive life.

In a format similar to the one above, students in the treatment group also received information about the earnings associated with university completion:

> In Mexico a man (woman) between 30 and 40 years old with a maximum education level of lower secondary earns, on average, $4,832 ($3,179) MX per month. A man (woman), ages 30 to 40, with a university degree earns, on average, $10,974 ($8,522) MX per month, or $6,143 ($5,343) MX more per month. Therefore a man (woman) with a university degree earns, on average, $3,350,035 ($2,914,064) MX more than a person with a lower secondary degree throughout his (her) productive life.

B. Data appendix: Administrative data sources merged with the original baseline survey

B.1. 9th grade ENLACE scores

Mexican citizens have a unique personal identifier, known as *Clave Única de Registro Poblacional, CURP*, formed by an algorithm combining name, surname, date of birth, sex, state of birth, plus two randomly generated digits. Using a student's personal information collected during the baseline survey we were able to generate a quasi-*CURP* that differs from the real one only in the lack of the last two randomly generated digits making possible a merge between the baseline survey with the micro data from ENLACE 9th grade. With the quasi-*CURPs* in hand, we were able to merge the baseline survey with the micro data from the 2009 and 2008 ENLACE 9th grade. In this way we recovered the 9th grade ENLACE scores for 75.5 percent of the 4145 students in our sample.[34] There are two potential explanations for the partial attrition of 9th grade scores: (1) the exam is voluntary and students enrolled in high school might have not taken it, and (2) matching issues arose either because we could not generate a quasi-*CURP* or there were multiple individuals with the same identifier. However, only for five individuals out of 4145 we were not able to generate a quasi-*CURP*.

B.2. 12th grade ENLACE scores

There are four possible explanations for why a student who was enrolled in EMS in 2009 did not take the 12th grade ENLACE exam in 2012: (1) the student dropped out of school at some point between 9th and 12th grade, (2) the student repeated one or more semesters, (3) the student did not show up for the exam but regularly completed the EMS, or (4) or potential merging problems. Only 205 students from the original sample (4.9 percent) took the exam in 2013, thus suggesting that the share of students who delayed the exam because of grade repetition is low. Nevertheless, the share of students belonging to the original sample who took the exam in 2013 is not statistically different for treatment and control schools. Two months before the test, all the schools participating in the test are required to send a list of students enrolled. Only for 2012, we collected individual level information on the students that were supposed to take the test, at each school and we measured the no-show rate. On average, 5 percent of the students reported on the list did not show up for the exam, but they were likely to complete EMS on schedule. Reassuringly, the no-show rate is not statistically different for treatment and control schools. Students who were surveyed at the baseline were matched with the 2012 and 2013 12th grade ENLACE results using an algorithm identical to the one described in section B.1. Also in this case, five students could not be identified by the quasi-*CURP* because it was not unique. Therefore, we interpret the difference in probability of taking the 12th grade exam between the treatment and control groups as a good measure of the intervention's effect on the probability of finishing high school on time.

In our sample, 730 students answered the *ENLACE de contexto*. The question reads exactly the same as the one asked in the baseline survey, but the students answer using a pre-codified set of brackets.[35] The *ENLACE de contexto* also elicits self-reported assessment of student effort. The respondent is asked how the statement "I am a person who works hard in school" describes him or her in one of the following ways: (1) it does not describe me at all, (2) it describes me a little bit, (3) it describes me, (4) it describes me a lot, or (5) it fully describes me. Students are also asked which subtrack they chose as part of the technological school curriculum and about their educational aspirations.

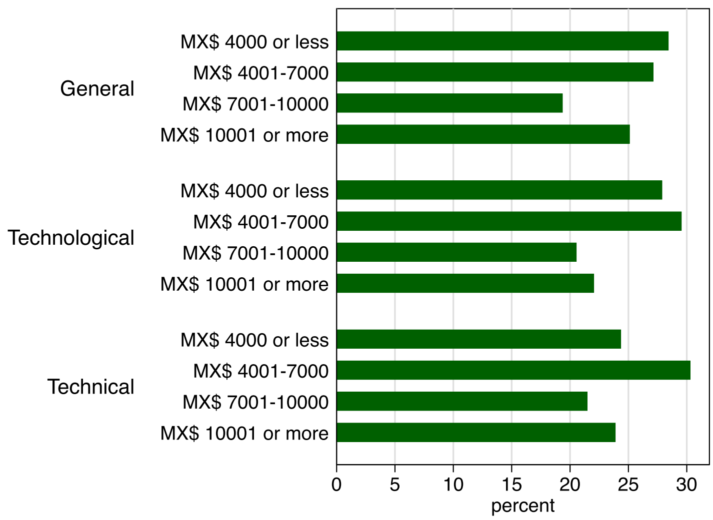
[33] In November 2009 $1 MX was approximately $0.08 US.

[34] Students who could be matched with 9th grade score are different from those who could not be matched along some dimensions (see Table AIII) but most differences are economically small.

[35] The earnings brackets for both questions are: i) $4000 MX or less; ii) $4001 MX to $7000 MX; iii) $7001 MX to $10,000 MX; iv) $10,001 MX to $15,000 MX; v) $15,001 MX to $20,000 MX; and vi) more than $20,000 MX.

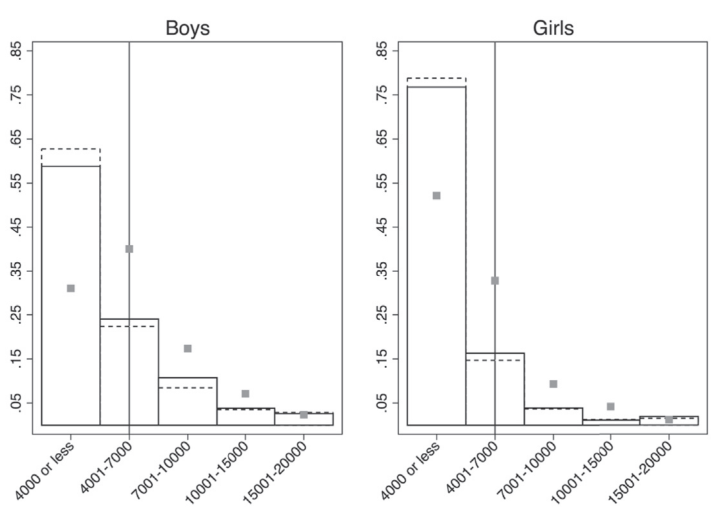
B.3. EXANI-II

We merge the original sample of 4145 with 2013 and 2012 EXANI-II data. The EXANI-II is a multiple choice test and consists of 110 questions–with 100 counting for the final score and 10 used as a test–in four subject areas: mathematics, analytical thinking, language structure and reading comprehension. There are 25 items for each of the four areas. In 2012 and 2013, 660,380 and 729,961 took the EXANI-II. Among those who took the test, 555,805 and 644,445 students ended up enrolling in the first year of university. While students who take the EXANI-II have a high probability of enrolling in the first year of university, there is a significant large fraction of students enrolled in first year of university who have not taken the EXANI-II. In 2012, out of 792,795 students who had taken the test, 70.11 percent had taken the EXANI-II. The share goes to 73.44 percent in 2013. We use the probability of taking the EXANI-II as proxy for the probability of enrolling in university. While it is unlikely that students in our sample would go to highly selective private university, we might potentially miss those students who enrolled in non-selective public or private universities.



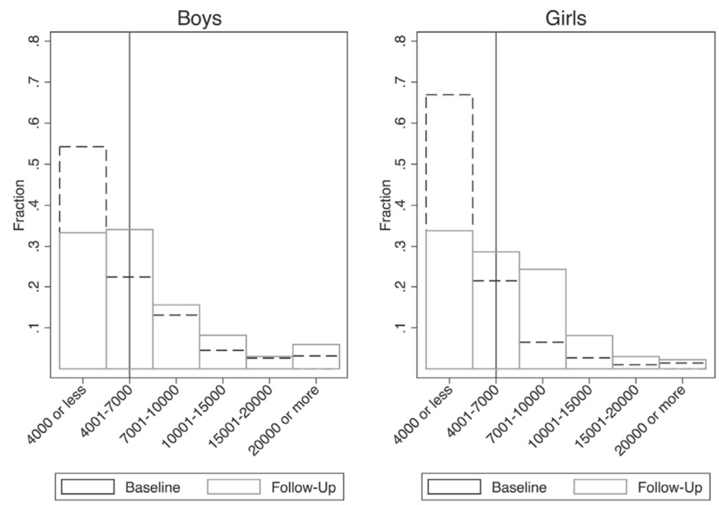
Note: Expectations about their own future earnings upon finishing high school among 12th grade students as elicited in the 2009 *ENLACE de contexto*. Expectations are reported in pre-specified brackets. The sample is restricted to students from urban areas.

Fig. AI. Monthly Expected Earnings upon finishing High School by High School Type.



Note: The histogram with the solid line plots the beliefs for the Treatment group. The histogram with the dash line plots the beliefs for the Control group. The scatter plots the observed earnings distribution based on data from the ENOE second quarter of 2009. The vertical line is in correspondence with the statistic provided to the students in the treatment group, and it is equal to the average monthly earning for high school graduates aged between 30 and 40 using data from ENOE second quarter of 2009. The baseline expected earnings for the average person upon finishing high school were elicited as part of the baseline survey conducted in November 2009.

Fig. AII. Baseline Monthly Expected Earnings (Average) upon finishing High School.



Note: The sample is restricted to boys and girls in the Control group. The baseline expected (own) earnings have been discretized using the thresholds used in the follow-up data source.

Fig. AIII. Comparison of Baseline and Follow-Up Monthly Expected Earnings (Own) upon finishing High School.

Table AI
Student characteristics by high school type.

	(1) General	(2)	(3) Technological	(4)	(5) Technical	(6)
	Mean	SD	Mean	SD	Mean	SD
Male	0.44	0.50	0.47	0.50	0.53	0.50
Scholarship	0.38	0.49	0.45	0.50	0.46	0.50
Currently Works	0.23	0.42	0.23	0.42	0.27	0.45
Spanish grade above 9 in lower sec	0.43	0.49	0.44	0.50	0.36	0.48
Math grade above 9 in lower sec	0.30	0.46	0.31	0.46	0.25	0.43
Father with Upper Secondary	0.17	0.37	0.17	0.37	0.16	0.37
Father with Higher Ed	0.33	0.47	0.23	0.42	0.18	0.38
Mother with Upper Secondary	0.15	0.36	0.14	0.35	0.13	0.34
Mother with Higher Ed	0.30	0.46	0.19	0.40	0.16	0.37
Household Appliances [1–5]	4.20	1.16	4.14	1.15	4.12	1.18
PC at home	0.95	0.23	0.94	0.23	0.93	0.25
Has more than 25 books	0.53	0.50	0.45	0.50	0.42	0.49
Smokes	0.31	0.46	0.30	0.46	0.35	0.48
Drinks	0.58	0.49	0.58	0.49	0.61	0.49
N	54283		61774		36244	

Note: We report the mean of each variable, and its standard deviation in parentheses. The sample includes the individuals who answered the 12th grade *ENLACE de contexto* in 2009. All the answers are based on pre-codified set of brackets, and we convert them into dummy variables. Spanish(Math) grade above 9 in lower sec reports the share of individuals who obtained a grade equal or above 9 on a scale between 6 and 10 in Spanish(Math) in the last year of lower secondary. The number of household appliances can take a value between 1 and 5.

Table AII
Evolution of gender differences in learning in Mexico.

	(1) Boys	(2) Girls	(3) Total	(4) N	(5) Boys-Girls
ENLACE 6th Grade					
Spanish	497.115	528.142	512.425	1,985,852	−31.03***
	(104.940)	(102.914)	(105.097)		
Math	505.488	522.422	513.844	1,985,852	−16.93***
	(112.061)	(108.299)	(110.545)		
ENLACE 9th Grade					
Spanish	491.835	523.131	507.953	1,389,773	−31.30***
	(103.799)	(102.705)	(104.415)		
Math	520.628	529.398	525.145	1,389,773	−8.770***
	(113.688)	(105.173)	(109.473)		
ENLACE 12th Grade					
Spanish	498.914	523.697	512.379	630,311	−24.78***
	(96.632)	(88.927)	(93.345)		
Math	600.302	570.487	584.103	629,975	29.81***
	(118.871)	(114.853)	(117.646)		

Note: We report the mean of each variable, and its standard deviation in parentheses. The sample includes the individuals who took the ENLACE 6th grade in 2007 nationwide, and we follow them through 9th grade (in 2010) and 12th grade (2013). *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table AIII
Comparing characteristics of matched and unmatched observations.

Variable	(1) Matched	(2)	(3) Unmatched	(4)	(5) M = U	(6)
	Mean	SD	Mean	SD	P-value	N
Male	0.55	0.50	0.50	0.50	0.007	4145
Age	16.71	1.27	16.42	0.66	0.000	4145
HH People	5.30	1.78	5.17	1.74	0.039	4141
Father works	0.86	0.35	0.84	0.37	0.118	4145
Mother works	0.45	0.50	0.47	0.50	0.187	4145
Father with primary ed.	0.31	0.46	0.30	0.46	0.865	3837
Mother with primary ed.	0.33	0.47	0.32	0.47	0.359	4018
Father with secondary ed.	0.38	0.49	0.36	0.48	0.165	3837
Mother with secondary ed.	0.43	0.50	0.39	0.49	0.023	4018
Father with high school or higher	0.31	0.46	0.34	0.47	0.112	3837
Mother with high school or higher	0.23	0.42	0.29	0.45	0.001	4018
Heater	0.61	0.49	0.64	0.48	0.095	4145
Washing Machine	0.78	0.42	0.79	0.41	0.424	4145
PC	0.52	0.50	0.58	0.49	0.002	4145
Internet	0.34	0.48	0.42	0.49	0.000	4131
Average share of homework handed in	0.80	0.20	0.83	0.19	0.000	4120
School days missed last month	2.72	2.36	2.68	2.36	0.780	1418
Sec. school qualification	8.38	0.80	8.51	0.82	0.000	4067
Failed any subject in sec. school	0.28	0.45	0.22	0.42	0.000	4133

Note: We report the mean of each variable, and its standard deviation in parentheses. Matched takes the value 1 if the student could be matched with the 2009 ENLACE results, 0 otherwise. The p-value on the test of equality is based on an OLS regression of the outcome of interest regressed on the match dummy.

Table AIV
Baseline characteristics of students who were administered the computer survey by treatment status.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Full Sample						Boys						Girls					
	Treatment		Control		T = C	N	Treatment		Control		T = C	N	Treatment		Control		T = C	N
	Mean	SD	Mean	SD	p-value		Mean	SD	Mean	SD	p-value		Mean	SD	Mean	SD	p-value	
PanelA: Baseline Survey																		
Male	0.53	0.50	0.51	0.50	0.586	3502												
Age	16.44	0.80	16.48	0.78	0.555	3502	16.52	0.87	16.57	0.87	0.592	1808	16.35	0.72	16.39	0.66	0.482	1694
HH Members	5.15	1.71	5.23	1.77	0.545	3500	5.16	1.70	5.17	1.61	0.948	1807	5.14	1.72	5.29	1.92	0.332	1693
Father works	0.83	0.37	0.85	0.36	0.346	3502	0.87	0.34	0.86	0.35	0.632	1808	0.79	0.41	0.84	0.37	0.091	1694
Mother works	0.48	0.50	0.46	0.50	0.349	3502	0.47	0.50	0.45	0.50	0.651	1808	0.50	0.50	0.46	0.50	0.164	1694
Father primary ed.	0.28	0.45	0.31	0.46	0.448	3240	0.26	0.44	0.29	0.45	0.432	1685	0.31	0.46	0.34	0.47	0.574	1555
Mother primary ed.	0.30	0.46	0.33	0.47	0.400	3397	0.27	0.44	0.32	0.47	0.245	1738	0.33	0.47	0.34	0.48	0.709	1659
Father secondary ed.	0.36	0.48	0.37	0.48	0.857	3240	0.37	0.48	0.37	0.48	0.974	1685	0.35	0.48	0.37	0.48	0.739	1555
Mother secondary ed.	0.39	0.49	0.41	0.49	0.461	3397	0.41	0.49	0.40	0.49	0.721	1738	0.38	0.49	0.43	0.50	0.140	1659
Father with high school or higher	0.36	0.48	0.32	0.47	0.356	3240	0.37	0.48	0.34	0.47	0.435	1685	0.34	0.47	0.30	0.46	0.365	1555
Mother with high school or higher	0.31	0.46	0.25	0.44	0.205	3397	0.32	0.47	0.28	0.45	0.332	1738	0.29	0.45	0.23	0.42	0.188	1659
Heater	0.67	0.47	0.64	0.48	0.561	3502	0.70	0.46	0.64	0.48	0.288	1808	0.63	0.48	0.64	0.48	0.983	1694
Washing Machine	0.80	0.40	0.80	0.40	0.966	3502	0.83	0.38	0.81	0.39	0.619	1808	0.76	0.43	0.78	0.41	0.637	1694
PC	0.60	0.49	0.53	0.50	0.201	3502	0.63	0.48	0.57	0.50	0.226	1808	0.57	0.50	0.49	0.50	0.227	1694
Internet	0.43	0.50	0.37	0.48	0.268	3490	0.45	0.50	0.40	0.49	0.431	1805	0.42	0.49	0.33	0.47	0.201	1685
Average share of homework handed in	0.83	0.19	0.81	0.20	0.184	3483	0.81	0.19	0.78	0.20	0.079	1799	0.85	0.19	0.84	0.19	0.424	1684
School days missed last month	2.47	2.17	2.85	2.51	0.012	1202	2.61	2.31	2.88	2.53	0.185	623	2.32	2.00	2.82	2.49	0.023	579
Sec. school qualification	8.55	0.80	8.45	0.83	0.260	3439	8.39	0.80	8.25	0.81	0.128	1781	8.73	0.76	8.65	0.79	0.434	1658
Failed any subject in sec. school	0.23	0.42	0.24	0.43	0.743	3491	0.29	0.46	0.30	0.46	0.986	1804	0.16	0.37	0.18	0.38	0.365	1687
Panel B: 9th grade ENLACE Outcomes																		
ENLACE in 2009	0.71	0.45	0.65	0.48	0.194	3502	0.66	0.48	0.64	0.48	0.675	1808	0.77	0.42	0.67	0.47	0.056	1694
ENLACE in 2008	0.07	0.25	0.05	0.22	0.331	3502	0.09	0.28	0.06	0.23	0.075	1808	0.04	0.20	0.05	0.22	0.462	1694
Language Score	534.21	98.40	526.54	97.46	0.578	2628	516.31	97.85	507.35	98.70	0.488	1327	552.74	95.57	545.83	92.35	0.652	1301
Language Insufficient	0.26	0.44	0.27	0.44	0.776	2628	0.32	0.47	0.34	0.47	0.722	1327	0.19	0.39	0.20	0.40	0.823	1301
Math Score	544.08	104.06	530.63	99.11	0.352	2628	537.69	103.90	525.76	101.22	0.397	1327	550.69	103.89	535.52	96.78	0.354	1301
Math Insufficient	0.45	0.50	0.49	0.50	0.521	2628	0.48	0.50	0.51	0.50	0.536	1327	0.43	0.50	0.47	0.50	0.559	1301

Note: We report the mean of each variable, its standard deviation in parentheses, the p-value on the difference between T and C and the number of observations. The p-value on the test of equality is based on an OLS regression of the outcome of interest regressed on the treatment dummy and the strata dummies, with standard errors clustered at school level. The sample is restricted to all students who had access to the computer laboratory and used the *Percepciones* interface.

Table AV
Correlates of the probability of taking the 12th grade ENLACE on time.

	(1)	(2)	(3)
	ENLACE 12 grade (Y/N)		
Male	−0.050**	−0.059**	−0.051**
	(0.022)	(0.024)	(0.023)
Age	−0.073***	−0.067***	−0.041**
	(0.014)	(0.015)	(0.016)
PC	−0.001	−0.005	−0.013
	(0.029)	(0.031)	(0.031)
Internet	0.047	0.043	0.029
	(0.031)	(0.033)	(0.033)
Father with Secondary	−0.045	−0.041	−0.040
	(0.028)	(0.030)	(0.029)
Father with High School or higher	−0.003	0.005	−0.009
	(0.032)	(0.034)	(0.033)
Mother with Secondary	−0.007	−0.005	−0.011
	(0.026)	(0.028)	(0.028)
Mother with High School or higher	−0.006	−0.022	−0.029
	(0.034)	(0.036)	(0.035)
Father works	0.011	0.020	0.031
	(0.043)	(0.045)	(0.044)
Mother works	−0.010	−0.019	−0.013
	(0.023)	(0.024)	(0.024)
9th grade Math ENLACE			0.055***
			(0.019)
9th grade Spanish ENLACE			0.038*
			(0.020)
Monthly HH Income Quartile Dummies	No	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Subsystem Fixed Effects	Yes	Yes	Yes
N	1913	1668	1643
Adj. R^2	.102	.093	.146

Note: The sample is restricted only to students in the control group. The dependent variable takes the value 1 if the student took the ENLACE exam in 2012, 0 otherwise.

Table AVI
Baseline characteristics of 12th grade ENLACE exam takers by treatment status.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Full Sample						Boys						Girls					
	Treatment		Control		T = C	N	Treatment		Control		T = C	N	Treatment		Control		T = C	N
	Mean	SD	Mean	SD	p-value		Mean	SD	Mean	SD	p-value		Mean	SD	Mean	SD	p-value	
PanelA: Baseline Survey																		
Male	0.48	0.50	0.49	0.50	0.873	2531						1221						1310
Age	16.39	0.84	16.39	0.69	0.999	2531	16.46	0.96	16.45	0.77	0.870	1221	16.32	0.72	16.33	0.60	0.815	1310
HH Members	5.14	1.68	5.23	1.77	0.628	2529	5.13	1.69	5.15	1.57	0.938	1219	5.15	1.68	5.30	1.94	0.503	1310
Father works	0.85	0.35	0.86	0.35	0.984	2531	0.88	0.32	0.85	0.36	0.054	1221	0.83	0.38	0.86	0.34	0.151	1310
Mother works	0.48	0.50	0.45	0.50	0.319	2531	0.45	0.50	0.43	0.50	0.665	1221	0.51	0.50	0.47	0.50	0.181	1310
Father with primary ed.	0.27	0.45	0.32	0.47	0.322	2357	0.25	0.43	0.29	0.46	0.384	1137	0.29	0.46	0.35	0.48	0.338	1220
Mother with primary ed.	0.29	0.45	0.34	0.47	0.334	2456	0.28	0.45	0.31	0.46	0.593	1170	0.30	0.46	0.36	0.48	0.218	1286
Father with secondary ed.	0.36	0.48	0.34	0.47	0.704	2357	0.35	0.48	0.36	0.48	0.944	1137	0.36	0.48	0.33	0.47	0.520	1220
Mother with secondary ed.	0.38	0.48	0.40	0.49	0.356	2456	0.37	0.48	0.41	0.49	0.247	1170	0.38	0.49	0.39	0.49	0.715	1286
Father with high school or higher	0.37	0.48	0.33	0.47	0.481	2357	0.40	0.49	0.35	0.48	0.390	1137	0.35	0.48	0.32	0.47	0.609	1220
Mother with high school or higher	0.33	0.47	0.26	0.44	0.174	2456	0.35	0.48	0.28	0.45	0.209	1170	0.32	0.47	0.25	0.43	0.197	1286
Heater	0.67	0.47	0.58	0.49	0.172	2531	0.70	0.46	0.59	0.49	0.119	1221	0.64	0.48	0.57	0.49	0.311	1310
Washing Machine	0.80	0.40	0.76	0.43	0.509	2531	0.82	0.38	0.77	0.42	0.196	1221	0.77	0.42	0.76	0.43	0.952	1310
PC	0.63	0.48	0.55	0.50	0.167	2531	0.66	0.47	0.56	0.50	0.151	1221	0.61	0.49	0.53	0.50	0.252	1310
Internet	0.47	0.50	0.38	0.49	0.211	2520	0.49	0.50	0.40	0.49	0.231	1220	0.46	0.50	0.37	0.48	0.238	1300
Average share of homework handed in	0.87	0.16	0.85	0.17	0.107	2516	0.85	0.16	0.82	0.17	0.042	1212	0.88	0.16	0.87	0.17	0.541	1304
School days missed last month	2.16	1.93	2.39	1.92	0.144	705	2.36	2.27	2.30	2.01	0.785	339	1.99	1.57	2.47	1.84	0.010	366
Sec. school qualification	8.74	0.74	8.64	0.76	0.289	2484	8.61	0.77	8.47	0.75	0.185	1201	8.86	0.69	8.79	0.74	0.517	1283
Failed any subject in sec. school	0.16	0.37	0.18	0.38	0.526	2524	0.20	0.40	0.20	0.40	0.980	1219	0.12	0.33	0.15	0.35	0.279	1305
Panel B: 9th grade ENLACE Outcomes																		
ENLACE in 2009	0.80	0.40	0.76	0.43	0.280	2531	0.75	0.43	0.74	0.44	0.899	1221	0.85	0.36	0.78	0.41	0.107	1310
ENLACE in 2008	0.05	0.21	0.04	0.19	0.497	2531	0.06	0.24	0.04	0.20	0.193	1221	0.03	0.18	0.04	0.19	0.786	1310
Language Score	551.55	96.62	539.19	93.63	0.384	2113	537.93	95.70	520.73	97.28	0.228	993	563.26	95.95	556.10	86.86	0.674	1120
Language Insufficient	0.20	0.40	0.22	0.42	0.643	2113	0.25	0.43	0.30	0.46	0.349	993	0.16	0.37	0.15	0.36	0.723	1120
Math Score	561.90	101.96	544.39	95.76	0.228	2113	561.69	102.57	544.85	96.88	0.248	993	562.08	101.52	543.97	94.82	0.262	1120
Math Insufficient	0.37	0.48	0.44	0.5	0.284	2113	0.37	0.48	0.44	0.50	0.195	993	0.38	0.49	0.43	0.50	0.446	1120

Note: We report the mean of each variable, its standard deviation in parentheses, the p-value on the difference between T and C and the number of observations. The p-value on the test of equality is based on an OLS regression of the outcome of interest regressed on the treatment dummy and the strata dummies, with standard errors clustered at school level. The sample is restricted to only those who took the ENLACE 12th grade exam in 2012.

Table AVII
High school outcomes either in 2012 or 2013.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ENLACE in 2012 or 2013 (Y/N)		Spanish		Math		Average Score	
Treatment	0.040	0.021	0.162	0.144	0.326**	0.309**	0.245**	0.227**
	(0.035)	(0.029)	(0.121)	(0.102)	(0.147)	(0.136)	(0.123)	(0.108)
Male	−0.033**	−0.021	−0.038	−0.002	0.352***	0.361***	0.159***	0.183***
	(0.015)	(0.015)	(0.035)	(0.034)	(0.036)	(0.035)	(0.029)	(0.028)
High HH Income	−0.006	−0.008	0.140***	0.113***	0.093***	0.077**	0.115***	0.093***
	(0.016)	(0.015)	(0.041)	(0.040)	(0.032)	(0.031)	(0.033)	(0.032)
Suff. Math readiness		0.104***		0.377***		0.496***		0.433***
		(0.022)		(0.040)		(0.045)		(0.035)
Suff. Spanish readiness		0.080***		0.542***		0.211***		0.373***
		(0.023)		(0.058)		(0.051)		(0.048)
Strata	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4145	4145	2735	2735	2735	2735	2735	2735
Mean Dep. Control Group	0.641	0.641	0.001	0.001	0.001	0.001	0.001	0.001
SD Dep. Control Group	0.480	0.480	1.000	1.000	1.000	1.000	0.882	0.882

Note: Robust standard errors clustered at school level in parentheses. The full set of controls (both displayed and not displayed) includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing. *ENLACE in 2012 or 2013 (Y/N)* takes the value 1 if the student took the 12th grade exam either in 2012 or 2013, 0 otherwise. *Spanish* and *Math* refer to the 12 grade ENLACE scores in Spanish and math in 2012 or 2013 and they have been normalized with respect to the mean and the standard deviation in the control group in the specific year. The *Average Score* is the average of the normalized scores in Spanish and math. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table AVIII
Baseline characteristics of 12th grade ENLACE exam takers by HH income and treatment status.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Low Income						High Income						Missing Income					
	Treatment		Control		T = C	N	Treatment		Control		T = C	N	Treatment		Control		T = C	N
	Mean	SD	Mean	SD	p-value		Mean	SD	Mean	SD	p-value		Mean	SD	Mean	SD	p-value	
PanelA: Baseline Survey																		
Male	0.42	0.49	0.47	0.50	0.285	924	0.54	0.50	0.51	0.50	0.440	1270	0.42	0.49	0.43	0.50	0.845	337
Age	16.45	1.08	16.42	0.68	0.776	924	16.37	0.69	16.38	0.71	0.782	1270	16.31	0.61	16.32	0.65	0.924	337
HH Members	5.21	1.80	5.27	1.90	0.462	923	5.15	1.65	5.23	1.73	0.918	1269	4.91	1.46	5.11	1.49	0.814	337
Father works	0.81	0.39	0.82	0.39	0.607	924	0.88	0.33	0.88	0.32	0.996	1270	0.88	0.33	0.86	0.35	0.489	337
Mother works	0.42	0.49	0.43	0.50	0.727	924	0.53	0.50	0.46	0.50	0.076	1270	0.49	0.50	0.46	0.50	0.653	337
Father with primary ed.	0.43	0.50	0.38	0.49	0.390	849	0.18	0.38	0.29	0.45	0.049	1210	0.18	0.39	0.32	0.47	0.044	298
Mother with primary ed.	0.42	0.49	0.43	0.50	0.575	899	0.21	0.41	0.27	0.45	0.325	1242	0.22	0.42	0.32	0.47	0.249	315
Father with secondary ed.	0.37	0.48	0.40	0.49	0.515	849	0.34	0.47	0.31	0.46	0.488	1210	0.37	0.49	0.30	0.46	0.173	298
Mother with secondary ed.	0.38	0.49	0.40	0.49	0.778	899	0.38	0.49	0.40	0.49	0.514	1242	0.35	0.48	0.41	0.49	0.261	315
Father with high school or higher	0.20	0.40	0.22	0.41	0.636	849	0.48	0.50	0.40	0.49	0.224	1210	0.45	0.50	0.38	0.49	0.453	298
Mother with high school or higher	0.20	0.40	0.17	0.38	0.341	899	0.41	0.49	0.33	0.47	0.254	1242	0.43	0.50	0.27	0.45	0.021	315
Heater	0.51	0.50	0.45	0.50	0.424	924	0.74	0.44	0.64	0.48	0.116	1270	0.81	0.39	0.70	0.46	0.116	337
Washing Machine	0.65	0.48	0.66	0.47	0.967	924	0.87	0.33	0.82	0.38	0.235	1270	0.88	0.32	0.82	0.39	0.373	337
PC	0.44	0.50	0.38	0.49	0.300	924	0.75	0.43	0.64	0.48	0.077	1270	0.71	0.46	0.63	0.48	0.407	337
Internet	0.25	0.44	0.21	0.41	0.379	916	0.60	0.49	0.49	0.50	0.210	1269	0.61	0.49	0.44	0.50	0.118	335
Average share of homework handed in	0.86	0.17	0.85	0.18	0.374	919	0.87	0.16	0.85	0.17	0.174	1263	0.88	0.14	0.85	0.19	0.281	334
School days missed last month	1.99	1.20	2.21	1.57	0.195	224	2.14	2.01	2.51	2.12	0.120	389	2.57	2.70	2.32	1.77	0.564	92
Sec. school qualification	8.68	0.74	8.59	0.76	0.251	910	8.80	0.74	8.67	0.77	0.256	1246	8.72	0.72	8.67	0.75	0.912	328
Failed any subject in sec. school	0.17	0.38	0.19	0.39	0.432	920	0.15	0.35	0.17	0.38	0.298	1268	0.19	0.39	0.14	0.35	0.258	336
Panel B: 9th grade ENLACE Outcomes																		
ENLACE in 2009	0.78	0.41	0.76	0.43	0.375	924	0.81	0.40	0.76	0.43	0.344	1270	0.83	0.38	0.77	0.42	0.317	337
ENLACE in 2008	0.05	0.22	0.04	0.20	0.604	924	0.05	0.22	0.03	0.18	0.214	1270	0.04	0.19	0.06	0.24	0.472	337
Language Score	530.08	94.07	525.25	90.40	0.747	767	564.12	95.99	547.85	94.66	0.338	1058	561.55	96.31	545.12	94.67	0.352	288
Language Insufficient	0.26	0.44	0.28	0.45	0.732	767	0.17	0.37	0.18	0.39	0.684	1058	0.19	0.39	0.21	0.41	0.941	288
Math Score	539.72	98.20	532.41	90.48	0.543	767	574.76	100.61	554.28	97.92	0.231	1058	572.68	106.75	539.35	98.34	0.068	288
Math Insufficient	0.46	0.50	0.47	0.50	0.749	767	0.32	0.47	0.40	0.49	0.184	1058	0.35	0.48	0.46	0.50	0.258	288

Note: We report the mean of each variable, its standard deviation in parentheses, the p-value on the difference between T and C and the number of observations. The p-value on the test of equality is based on an OLS regression of the outcome of interest regressed on the treatment dummy and the strata dummies, with standard errors clustered at school level. The sample is restricted to only those who took the ENLACE 12th grade exam in 2012.

Table AIX
Effect on perceived earnings by initial conditions.

	(1) Less than 4000	(2) Between 4000 and 7000	(3) Above 7000
Panel A: Heterogeneity by Readiness			
Treatment X Insuff. Math Readiness	−0.140**	0.110***	0.023
	(0.063)	(0.042)	(0.047)
Treatment X Suff. Math Readiness	−0.143**	−0.017	0.150***
	(0.061)	(0.046)	(0.050)
Treatment X Missing Math Readiness	−0.135*	0.153*	−0.004
	(0.070)	(0.083)	(0.112)
Strata Dummies	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	728	728	728
P-Value H_0: Insufficient Readiness = Sufficient Readiness	0.964	0.100	0.017
P-Value H_0: Insufficient Readiness = Missing Readiness	0.947	0.630	0.762
Panel B: Heterogeneity by HH Income			
Treatment X Low HH Income	−0.201***	0.111***	0.091
	(0.055)	(0.043)	(0.060)
Treatment X High HH Income	−0.044	0.005	0.033
	(0.062)	(0.048)	(0.079)
Treatment X Missing HH Income	−0.240***	0.104	0.135**
	(0.132)	(0.116)	(0.059)
Strata Dummies	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	728	728	728
P-Value H_0: Low Income = High Income	0.115	0.180	0.627
P-Value H_0: Low Income = Missing Income	0.818	0.955	0.561

Note: Robust standard errors clustered at school level in parentheses. The full set of controls includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing. The dummy *Less than $4000 MX* takes the value 1 for an expected monthly earning below $4000 MX upon finishing high school, 0 otherwise. The dummy *Between $4000 MX and $7000 MX* takes the value 1 for an expected monthly earning between $4000 MX and $7000 MX upon finishing high school, 0 otherwise. The dummy *More than $7000 MX* takes the value 1 for an expected earning above $7000 MX upon finishing high school, 0 otherwise. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table AX
Robustness tests.

	(1) ENLACE (Y/N)	(2) Spanish	(3) Math	(4) Average Score	(5) EXANI-II (Y/N)	(6) EXANI above 1150 (Y/N)
Panel A: OLS Results						
Treatment	0.008	0.125	0.303*	0.214*	0.053	0.024
	(0.031)	(0.114)	(0.154)	(0.126)	(0.040)	(0.029)
Male	−0.055***	−0.048	0.372***	0.162***	0.041**	0.056**
	(0.017)	(0.047)	(0.065)	(0.051)	(0.020)	(0.025)
High HH Income	0.006	0.175***	0.134**	0.154***	0.032	0.029
	(0.015)	(0.054)	(0.058)	(0.052)	(0.020)	(0.026)
Suff. Math Readiness	0.155***	0.539***	0.644***	0.592***	0.115***	0.117***
	(0.024)	(0.068)	(0.080)	(0.068)	(0.026)	(0.021)
Suff. Spanish Readiness	0.087***	0.655***	0.273***	0.464***	0.079***	0.041***
	(0.025)	(0.072)	(0.080)	(0.068)	(0.024)	(0.014)
Strata Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Table AX *(continued)*

	(1) ENLACE (Y/N)	(2) Spanish	(3) Math	(4) Average Score	(5) EXANI-II (Y/N)	(6) EXANI above 1150 (Y/N)
N	4145	2531	2531	2531	4090	898
Adj. R^2	0.118	0.198	0.190	0.225	0.079	0.055
Mean Dep. Control Group	0.598	0.000	0.000	0.000	0.246	0.071
SD Dep. Control Group	0.490	1.000	1.000	0.884	0.431	0.257
Panel B: Sample restricted to those with access to computer lab						
Treatment	0.011	0.118	0.308**	0.214*	0.034	0.018
	(0.031)	(0.111)	(0.147)	(0.115)	(0.040)	(0.028)
Male	−0.052***	0.023	0.348***	0.189***	0.050***	0.058***
	(0.017)	(0.042)	(0.038)	(0.032)	(0.017)	(0.022)
High HH Income	0.001	0.109**	0.078**	0.092***	0.008	0.027
	(0.016)	(0.043)	(0.035)	(0.034)	(0.018)	(0.026)
Suff. Math Readiness	0.122***	0.416***	0.505***	0.458***	0.083***	0.100***
	(0.023)	(0.049)	(0.046)	(0.039)	(0.025)	(0.020)
Suff. Spanish Readiness	0.089***	0.593***	0.239***	0.413***	0.077***	0.045***
	(0.026)	(0.067)	(0.061)	(0.056)	(0.024)	(0.013)
Strata Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	3502	2146	2146	2146	3458	796
Mean Dep. Control Group	0.602	0.032	0.037	0.035	0.252	0.074
SD Dep. Control Group	0.490	1.009	1.004	0.890	0.434	0.262

Note: Robust standard errors clustered at school level in parentheses. The full set of controls includes the macro-regions where the school is located (north, center and south), the level at which the randomization has been stratified, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), age and gender of the student, dummies for whether the level of proficiency in math and Spanish in the 9th grade ENLACE is at least sufficient, and a dummy for whether the 9th grade score are missing, a dummy for whether the student reports the monthly household income to be above $3500 MX, and a dummy for whether the information on household income is missing. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Appendix C. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jdeveco.2018.07.008.

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