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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

A randomized control trial was conducted to study whether providing 10th grade students with information about the returns to upper secondary and tertiary education, and a source of financial aid for tertiary education, can contribute to improve student performance. The study finds that the intervention had no effects on the probability of taking a 12th grade national standardized exam three years after, a proxy for on-time high school completion, but a positive and significant impact on learning outcomes and self-reported measures of effort. The effects are larger for girls and students from households with a relatively high income. These findings are consistent with a simple model where time discount determines the increase in effort and only students with adequate initial conditions are able to translate increased effort into better outcomes.

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The Heterogeneous Effect of Information on Student Performance: Evidence from a Randomized Control Trial in Mexico*

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1 Introduction

Early work for developing countries finds that providing information about the labor market returns to education had a positive impact on student attainments (Jensen 2010; Nguyen 2008).[1] These results, coupled with the low costs of these interventions, have induced scholars and policy makers to advocate for a more extensive usage of information interventions to boost students' outcomes in developing countries.[2] However, while there is growing con-

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[1]Jensen (2010) finds that providing information about the returns to lower secondary has a very large impact on school completion rates among eight graders in the Dominican Republic. Nguyen (2008) shows an increase in attendance of fourth graders in Madagascar as a result of information about the labor market returns to lower secondary education. More recently, Dinkelman and Martínez (2014) find that information about financial aid for tertiary education had a significant impact on college preparatory enrollment, school attendance, and financial aid knowledge among eight graders in Chile. Loyalka et al. (2013) finds that providing information on college costs and financial aid to high school students in poor regions of northwest China increases the probability of attending college.

[2]A number of studies analyze the impact of information about the benefits and costs of higher education on students' perceptions in developed countries (see, among others, Oreopoulos and Dunn (2013) for Canada and McGuigan et al. (2012) for the UK.)

sensus that quality - rather than quantity - of education is an important driver of economic growth (Hanushek and Woessmann 2008; Hanushek and Woessmann 2012), it is unclear whether information interventions can have long-lasting impact on student achievements. If students expect labor market returns lower than the observed ones, information interventions might be able to increase their effort, and ultimately improve their performance in school. Existing evidence shows either short term positive impact (Nguyen (2008) for Madagascar) or no impact (Fryer (2013) for the US) on learning in early grades.[3] This paper presents evidence from a randomized control trial conducted in Mexico to study whether an information intervention targeting 10th grade students had an impact on their performance in 12th grade.[4]

Mexico, as well as other middle-income countries, has reached almost universal enrollment rates in primary and lower secondary, but still faces important challenges in the education system, especially in upper secondary. Only six out of every ten students who enroll in upper secondary education graduate. Education achievements are characterized by large disparities, with those accounted for by gender being particularly striking. Although girls perform at least as well as boys throughout primary and lower secondary education in all subjects, as witnessed by their scores in 6th and 9th grade national census based standardized test - *Evaluación Nacional de Logro Académico en Centros Escolares* (ENLACE), girls fall dramatically behind boys in 12th grade math scores (see Table 1). While the quality of school supply might play an important role, there is not full clarity on the individual characteristics that can explain the attainment and the achievement gaps. Financial constraints, lack of information and social norms may be important demand side factors behind the high drop out and low learning outcomes, but disentangling their role is empirically challenging.

In 2009 the Mexican Secretariat of Public Education (SEP for its acronym in Spanish), in an attempt to improve on-time graduation and learning outcomes in upper secondary, designed and implemented an intervention to provide students entering 10th grade with a range of information about the returns to upper secondary and tertiary education, as well as on life expectancy and funding opportunities for tertiary education. The pilot program, known as *Percepciones*, 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 administrative data from the 12th grade national standardized EN-

[3]Nguyen (2008) shows an increase in test scores of fourth graders in Madagascar three months after the intervention. Fryer (2013) finds no impact on student scores in sixth and seventh grade.

[4]Throughout the paper we will use upper secondary education and high school indifferently when we refer to grades 10 to 12. We will use lower secondary when referring to grades 7 to 9.

LACE exam, we measure the impact of the information treatment on a proxy for completing upper secondary on time and standardized test scores in math and language (Spanish). We shed light on some of the behavioral responses induced by the intervention using information from a survey that was administered at the time of the test to a random sample of exam takers.

Our results show that, almost three years after the treatment was implemented the information package had no impact on the proxy for completing high school on time. On average, the intervention had a large and statistically significant impact on math test scores (0.29 standard deviations), and a positive but not statistically significant impact on language scores. A more detailed analysis shows that the treatment had a large and significant effect on the learning outcomes of female students and those who belong to relatively better off households. Both boys and girls update their expectations as a result of the intervention, but only girls report a higher level of effort and switch to more demanding upper secondary subtracks, with higher expected returns in the labor market. Neither the initial level of information about returns to education nor differences in time preferences seem to explain much of the differential effect for boys and girls. There is also no evidence that the gender related heterogeneity is driven by gender-specific parents' or teachers' responses. We conjecture that at least in the sample we consider, boys have lower scope to increase their effort. The stronger impact on better-off students is consistent with the hypothesis that the increase in effort can translate into better learning outcomes only if complemented with sufficient initial conditions as proxied by household income.

The contribution of this paper is twofold. First we contribute to a better understanding of the effects of information on different educational outcomes. The very large and significant effects on school attainments in rural Dominican Republic (Jensen 2010) and Madagascar (Nguyen 2008) contrast with the zero impact found for the US (Fryer 2013), China (Loyalka et al. 2013) and Mexico in this paper. In low income countries, providing information about school returns might be sufficient to induce at-risk students to stay in school since the alternative option may be particularly low. However, in medium and high income countries, the higher probability of finding a paid job might induce at-risk students to drop out, irrespective of how well informed they are.[5] Unlike previous work, we provide evidence on the impact of information on learning at the end of high school, an outcome that is likely to be correlated with youth labor market outcomes (Murphy and Peltzman 2004). The aver-

[5]Atkin (2012) finds for Mexico that the employment opportunities for low-skill workers in the manufacturing sector generated by trade liberalization had significant consequences on school drop-out: for every twenty new jobs created in the manufacturing sector, one student dropped out at grade nine rather than continuing on through grade twelve.

age impact is non-negligible and statistically significant, and given the virtually zero cost of the intervention this result provides further support to the cost-effectiveness of information interventions.

In many disadvantaged contexts educational choices made by girls are likely to be affected by social norms, rather than potential labor market outcomes.[6] Information interventions as the one included in the *Percepciones* program can be an effective way of changing girls' educational choices, improve their learning outcomes and, eventually their labor market outcomes.

The paper is organized as follows. Section 2 presents general information regarding the upper secondary education system in Mexico and a description of the information treatment within the *Percepciones* project. In Section 3 we discuss a simple framework to describe how information can affect student performance together with the data used for our analysis. The econometric model and the main results are presented in Section 4. Potential explanations for the large gender heterogeneity are discussed in Section . Finally, Section 6 concludes and provides policy recommendations.

2 Context

The upper secondary education (EMS for its acronym in Spanish) system in Mexico consists of 4.1 million students, typically between 15 to 18 years old, in grades 10th, 11th and 12th. EMS is offered by four different providers: 1) the federal government (accounting for 26% of total enrollment), 2) the state government (43.8%), 3) publicly-financed autonomous universities (12.5%), and 4) private entities. EMS offers three types of degree programs: *general* – preparing students for higher education, *technological* – preparing students both for the labor market as well as for higher education, and *technical* – emphasizing technical and vocational education. The typically large technological schools run by the Federal Government (930 students on average) can belong to different subsystems according to their specialization: industrial (DGETI), agricultural (DGETA) and ocean-related (DGCYTM).

According to the official statistics from SEP,[7] in 2013 only 61% of students graduated three years after enrolling, with this share being significantly higher among women (65%) than men (57%). Graduation rates vary across types of degree programs with *general* schools

[6] Attanasio and Kaufmann (2012a) found for Mexico that educational choices of boys are more likely to be correlated with expectations on the labor market returns of higher education than girls' expectations, which display a stronger correlation with their aspirations to form a family. 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.

[7] See http://www.inee.edu.mx/index.php/bases-de-datos/banco-de-indicadores-educativos

showing the highest (64%), followed by *technological* schools with rates very close to the national average and *technical* schools showing the lowest (48%). More than 60% of the cumulative dropouts throughout the three years of EMS take place during the first year. The decision behind early drop out can be partly explained by the combination of high risk of repetition (the average grade repetition rate was about 15% in 2013) and the strict promotion criteria used in EMS. Students must pass five out of eight disciplinary subject areas and practical modules, otherwise they have to repeat the semester. Additionally, students must pass all their subject areas and modules (around eight in total per semester) within ten semesters after enrolling in EMS, otherwise they lose the right to re-enroll.

The *Percepciones* pilot took place in 54 technological EMS schools run by the Federal Government. The objective of the *Percepciones* pilot was to evaluate the effectiveness of a low cost information intervention to increase on-time high school graduation and increase learning outcomes. The design of the *Percepciones* project benefited substantially from the survey collected in 2005 as part of the evaluation of the Mexican program *Jóvenes con Oportunidades*. The 2005 survey showed that there was a misperception about the returns to education when compared to the returns from the labor survey ENOE (*Encuesta Nacional de Ocupación y Empleo*), especially among girls, thus providing scope for the intervention.[8] A randomized control trial was designed to evaluate the impact of the intervention. Figure 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 allocated into 26 treatment schools and 28 control schools. The selected schools had an average of 8 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 4,145 students were included in the experiment.[9]

2.1 Description of the Treatment

The intervention was conducted in November 2009 (Figure 1). An interactive computer software, designed explicitly for the project, gathered information on students' perceived returns to schooling and, in the case of the treatment group, provided the information package. Given the design of the intervention, all of the students in the treatment group

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

[9]For two schools the first two randomly selected classrooms were too small, and additional classrooms had to be selected.

who completed the baseline survey were exposed to the information, thus guaranteeing *perfect compliance*.

In order to elicit the information on perceived returns to schooling, the computer software used three subjective expectation questions, similar to the ones included in the *Jóvenes con Oportunidades* survey:

1. If you were to quit studying right now and hence lower secondary is your highest degree, what do you think is the amount you can earn per month at ages 30 to 40?

2. If you finish upper secondary and do not continue studying, what do you think is the amount you can 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 can earn per month at ages 30 to 40?

Similarly, the computer software elicited information about the students' perception about the returns to schooling for an average person, as opposed to expectations about his or her own returns.[10] Students in the treatment group received three main information contents. First, they were given gender-specific information on the monetary returns to schooling, as computed using data from ENOE second quarter of 2009. The information on the returns to education was given in the form of additional monthly pesos earned by upper secondary working full time as well as the net present value of the additional income flows assuming entry and exit to the labor market at ages 25 and 65, respectively:

> 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.[11] A man (woman), ages 30 to 40, with an upper secondary 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 an upper secondary diploma earns, on average, \$784,320 (\$791,040) MX more than those with a lower secondary degree throughout his (her) productive life.

Students in the treatment group also received information about the returns to university in a format similar to the one presented above. The second type of information content

[10]The three questions read as follows: (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 an upper secondary 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?

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

is about a higher education scholarship program run by the federal government (PRONABES). While most of the Mexican higher education system is public and free of charge, the PRONABES program targets student from households with a monthly income equal to or below three minimum wages, and provides grants that vary from \$750 MX to \$1,000 MX per month for the entire length of the higher education course. Finally, students received information about life expectancy (differentiated by gender). Additionally, a 15-second video summarizing the message that youth can empower themselves with education was shown to the students in the treatment group.

Most of the interventions that have been previously tested provide information either on the expected financial returns of education (Jensen 2010; Nguyen 2008) or on the sources of financial aid (Dinkelman and Martínez 2014).[12] The *Percepciones* project gave students an information package, that covers the financial returns of secondary and tertiary education, one source of financial aid for tertiary education and life expectancy. The intervention's design does not allow for the assessment of whether our results are driven by any specific piece of information or by the entire package.

3 Conceptual Framework and Data

3.1 Conceptual Framework

We borrow the simple two period framework presented in Fryer (2013) to help rationalize the linkages between the information intervention and student outcomes. Student's education outcomes (S) at time t is a function (f) of her/his effort (e) and a set of predetermined characteristics (μ_0), that include, among others, parental education, household income, and neighborhood characteristics.

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

Mirroring Fryer (2013), we assume that: a) f is twice continuously differentiable in e and μ_0; b) f exhibits diminishing marginal returns to e; c) e and μ_0 are complements in the education production function. At time $t+1$ the student enters the labor market and his/her labor market outcomes (Y) are a function of the school outcomes at time t and a parameter (ν), that measures students' perceived returns to education outcomes. Both attainments and performance in school are likely to affect Y. We assume that earnings are increasing in

[12] 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.

S, although at a declining rate. Increases in the perceived returns, ν, increase Y at all levels of S.

$$max_e \left[\beta \left[Y_{i,t+1}(S_{i,t}(e_{i,t}), \nu)\right] - C(e_{i,t})\right] \tag{2}$$

The individual chooses effort at time t maximizing the future earnings discounted at the time discount rate β, minus the cost of effort ($C(e)$). In this very simple setting, information about returns to education will increase the optimal level of effort to the extent that: a) the student's perceived returns are significantly lower than the actual returns; and b) the student places a significant value to future consumption (high β). However, an increase in effort does not necessarily generate an increase in student performance. In fact, if the complementarity between e and μ_0 does not hold and/or the student does not know how to translate increased effort into better outcomes, an increase in effort might not lead to improved performance.

3.2 Baseline Data

In order to measure students' characteristics at the baseline, we use two sources. First, we rely on the survey administered to the students in November 2009, just before the treatment was rolled out. In addition to providing information about the perceived returns to schooling, students were asked, among others, questions about the source of information about the returns, household income,[13] parents' education and work status. The baseline survey also included a module that elicits students' inter-temporal preferences. The respondent was asked to consider a hypothetical situation in which he/she wins a certain amount of money that can be cashed in now, or can be cashed in later for a larger sum.

Second, we use administrative data on 9th grade ENLACE scores in math and language to measure students' ability before entering high school. From 2007 to 2013, ENLACE was administered to all students in 3rd to 9th and 12th grades. The test is voluntary and bears no consequences either on graduation or a student's GPA. The score is normalized to have a mean of 500 and a standard deviation of 100. 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 2 randomly generated digits. Using the student's personal information collected during the baseline survey we could generate a quasi-*CURP* that only differs from the original one for the lack of the last

[13]Information regarding household income was reported in brackets as follows: 1) less than \$1,500 MX, 2) between \$1,501 and \$3500, 3) between \$3,501 and \$7,000, 4) between \$7,001 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% of the students, but the attrition rate is not statistically different for the treatment and control group.

two randomly generated digits making possible a merge between the baseline survey with the micro data from ENLACE 9th grade.[14] For 75.5% of the students in our sample, we can recover their 9th scores ENLACE score, with 68% taking the exam in 2009, 1.1% in 2007 and 0.4% in 2006.[15] There are two potential explanations for the partial attrition of 9th grade scores: 1) the exam is voluntary and students enrolled in upper secondary might have not taken it; 2) matching related issues either because the information provided during the baseline was not sufficient to generate the quasi-*CURP*, or for the presence of multiple individuals with the same identifier. Only for five individuals out of 4,145 we were not able to generate a quasi-*CURP*.

Table 2 shows the baseline characteristics, for the full sample as well as separately for boys and girls, distinguishing between students in the treatment and the control groups. In the top panel we report the socioeconomic characteristics measured through the baseline survey, 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. For boys we find that, out of 23 variables, only the probability that the father works is statistically higher in the treatment than in the control group (p-value=0.011), but the size of the difference is economically negligible. In order to account for these imbalances, our main specification controls for all the variables that display significant imbalances. On average, 93% of the fathers work, as opposed to 45% of the mothers; fathers tend to be more educated than mothers, since 31% of the formers have, at least, completed high school as opposed to 24% of the latter. About 40% of the students have access to an Internet connection at home.

Self-reported measures of effort do not display major differences between boys and girls, neither when we consider the number of hours spent doing homework (5.62 for boys and 5.11 for girls), nor when we look at the number of school days missed last month (2.8 for boys and girls). Girls report a much lower probability of having failed at least one subject in lower secondary school than boys (19% versus 30%).

Students in the treatment group are more likely to be matched with 9th grade test score results and the difference is marginally significant at 10%. In 9th grade girls perform better than boys in language, irrespective of whether we consider the test score or the probability of being classified as insufficient, and they do as well as boys in math (approximately 35% of them are classified as insufficient). Previous work using data from low- and middle-income

[14]Given that the *CURP* and the information to form the quasi-*CURP* is confidential, the merge between the baseline survey information and the micro information of ENLACE was done by staff at the SEP.

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

countries shows that the gender gap in math is present as early as 4th grade (Bharadwaj et al. 2012). This is not the case 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 (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' 12th grade score in math is 30 points (0.30σ) lower than boys' (Table 1). The gender gap in 12th grade may be partly explained by differential selection: 28.6% of the boys who took the ENLACE 6th grade in 2007 completed the 12 grade exam in 2013, as opposed to 34.9% of the girls.

3.3 Follow-up Data

Students enrolled in 10th grade in 2009 were supposed to complete high school in 2012.[16] 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. We interpret the probability of taking the 12th grade test in 2012 as a proxy for the probability of completing upper secondary on time. 61% of the students surveyed at the baseline took part in the 12th grade ENLACE exam three years later. Not observing a student who was originally enrolled in EMS in 2009 take part in the 12th grade ENLACE exam in 2012 has four possible explanations: 1) the student dropped out of school at any 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, 4) or potential merging problems. Using 2013 data from 12th grade ENLACE we find that 205 students from the original sample (4.9%) took the exam in 2013, most likely because they had to repeat two full semesters.[17] The probability of taking ENLACE in 2013 is not statistically different for treatment and control schools. In order to provide a measure of the no-showing up rate, we collected the 2012 lists of all the potential 12th grade ENLACE takers that each school had to send to the central authority roughly two months before the test. On average, 10% of the students reported on the list did not show up for the exam, but they are likely to complete EMS regularly. Reassuringly, the no-showing-up rate is not statistically different for treatment and control schools. Finally, only for five students the quasi-*CURP* was not sufficient to identify them since 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

[16]The northern State of Nuevo León is an exception since public upper secondary schools follow a two-year program.

[17]Students who repeat either one or three semesters leave school without taking the test.

the probability of finishing upper secondary on time.

In order to measure how expectations about the returns to education have changed in response to the intervention, we rely on the data from a nationwide survey administered to 20% of all 12th grade exam takers, the so called *ENLACE de contexto*. In our sample, 730 students were administered the *ENLACE de contexto*. The 2012 survey gathers, among others, information on expected monthly earnings at ages 30 to 40 on two hypothetical scenarios of educational attainments, high school completion and university degree. These questions read exactly the same as the ones asked in the baseline survey, but the answers are given using a pre-codified set of brackets.[18]

The *ENLACE de contexto* does not collect objective measures of student effort but it elicits self-reported assessment. 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, 5) it fully describes me. Students are also asked which subtrack they chose as part of the technological school curriculum.

3.4 Perceptions about Returns to Schooling

As discussed in section 2.1, the baseline survey asked both about student's own expected earnings and the student's expected returns for the average person. While variation in the perceived returns for oneself reflects both possible misperceptions about the education returns and heterogeneity in subjective valuations of how well oneself can do in the labor market, dispersion in perceived average returns would just reflect misperception. Table 3 reports the gender specific mean and standard deviation of the expected monthly wages for themselves and for the average person, separately for the treatment and the control group. For none of the measures of perceived returns, the difference between the treatment and the control group is statistically significant.[19]

At the baseline, the mean expected monthly wage for oneself, having completed high school as the highest degree, among boys in the control schools ($5,531 MX) is not statically different from the average wage for a man with high school degree between 30 and 40 using data from ENOE ($5,722 MX). When asked about the expected wage for an average man between 30 and 40, the average expected value is substantially lower ($4,282 MX). On

[18] The earnings brackets for both questions are: i) $4,000 MX or less; ii) $4,001 MX to $7,000 MX; iii) $7,001 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.

[19] The statistics displayed in Table 3 are generated trimming the top 1% and the bottom 1% of the earnings expectations, but the balancing properties still hold in the untrimmed sample.

average, a girl in the control group expects to earn \$4,101 MX, as opposed to an average estimated wage of \$4,827 MX for a woman with high school degree between 30 and 40 years old, according to ENOE. The average expected wage for the average woman is \$3,154 MX.

Comparing the mean expected wages with observed values might not be particularly meaningful in the presence of highly skewed expected income distributions. In order to better understand the extent of the misperceptions, we discretize the baseline answer applying the thresholds used in the follow-up data source - i.e. 12th grade *ENLACE de Contexto*. Figures 2 plots the distribution of expected wages (self) at the baseline against the observed distribution in the 2009 ENOE separately for boys and girls. The largest difference between perceived and observed earnings realizations are concentrated in the first two bins of the distribution; the fraction of both boys and girls who think that they will earn less than \$4,000 MX is much larger than the actual fraction of high school graduates earning 4,000 or less in the second trimester of 2009. For earnings higher than \$7,000 MX we do not observe significant differences between the distribution of the expected earnings (self) and the current ones. The extent of this misperception becomes even more evident when we consider the distribution of the expected earnings of an average person between 30 and 40 and compare it with ENOE (Fig. AI).

Both for boys and girls the income expectations upon completing university are on average higher than the wages observed for a university graduate between 30 and 40 years old, as measured in the ENOE data. This is true irrespective of whether or not we consider the income expectation for oneself or for the average person.

In summary, the average perception on the wages that each of them can earn upon completing upper secondary is aligned with the average wage observed in the labor market. However, there is a large fraction of boys and girls who tend to underestimate the earnings of a high school graduate in the labor market. According the to the baseline survey, 79% of the respondents mentioned family members as one of the three main sources of information about the benefits of studying, followed by television (70%) and internet (48%). In order to provide *prima facie* evidence on the link between expected earnings and school performance, Table 4 shows the correlation between baseline expectations about future earnings, expressed in logarithms, and follow-up outcomes for the individuals in control schools. The correlation between the expected log earning upon completing either upper secondary or tertiary education and the probability of being identified in the 2012 ENLACE 12th grade is small and not statistically significant, regardless of whether or not we consider the expectations for oneself or the average person. We do find evidence of a significant correlation between the expected earnings and the results in math and Spanish. The correlation is particularly strong and statistically significant when we consider the expectations for oneself (columns 5-6 and 9-10 in Table 4), rather than for the average person. Although the association does not have any causal interpretation, it does suggest that expectations of students upon entering high school, especially the ones for oneself, do bear some relation to final performance.

4 Empirical Analysis

4.1 Econometric Model

To estimate the causal impact of providing information about the labor market returns of educational attainments, we estimate the following equation:

$$Y_{ij} = \beta_0 + \beta_1 D_j + \gamma' X_{ij} + u_{ij} \tag{3}$$

where Y_{ij} is the outcome of student i in school j recorded in the follow-up survey. D_j is an indicator dummy that takes the value one if school j is assigned to the treatment group, 0 otherwise. β_1 measures the average treatment on the treated (ATT) 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 the level of proficiency in math and Spanish in the 9th grade ENLACE, and dummies for whether the 9th grade scores in math or Spanish are missing, dummies for whether the mother and the father work, dummies for whether the information on father's and mother's work status is missing, dummies to proxy for the presence PC and internet at home. In order to reduce the potential efficiency losses due to the multilevel 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) estimator. The results from the standard OLS, although slightly less precise, are in line with those presented and are available upon request. In all the specifications, standard errors are clustered at school level to account for correlated shocks within schools, that represent the level at which the treatment is assigned.

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 Education Outcomes

In this section we describe the results of our experiment on the four main education outcomes: the probability of taking the 12th grade ENLACE on time - i.e. three years after the start of upper secondary, standardized Spanish test score, standardized math test score and the average of the two. In Table 5 we present the ATT effects for the whole sample. In the odd columns we present the results for the specification that only controls for the strata dummies, in the even columns we show the results of our main specification with the full set of controls.

Receiving information about returns to education had a positive, but not statistically significant effect (coeff. 0.025 and standard error 0.042) on the probability of taking the ENLACE test in 2012, thus suggesting that the intervention did not affect on-time high school completion. In principle, if information about school returns is increasing students' incentives, we might have expected a higher probability of completing high school on time.

We next consider the effect on students' learning outcomes. The results are presented in columns 3 to 8 in Table 5. The treatment effect is equal to 0.16σ and not statistically significant for Spanish and 0.32σ and marginally significant for math when we only control for the strata dummies. For the average of the two scores, we find an effect of 0.24σ, statistically significant at 10% level. When we include the full set of controls, the effect of the information treatment is equal to 0.10σ (not statistically significant) for Spanish, 0.29σ for math (significant at 5%) and 0.20σ (significant at 10%) for the average score. 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 are driven by differential selection into the ENLACE exam in treatment and control schools.

We next consider how the treatment effect varies with three important dimensions: gender, ability and household income. The experiment was not designed to be representative at any of this level. 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.[20] We study whether boys and

[20]Increased life expectancy should increase the incentive to invest in schooling since a longer time horizon

girls responded differentially to the information provision. Results are presented in Panel A in Table 6. In the control group, girls are more likely to take the test than boys (63% vs 57%). 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. In the control group, 12th grade girls' scores in language are better then boys' but their scores in math are about 0.40σ lower than for boys. This is somehow striking since the 9th grade score in math of the girls in the control group was 533 points as opposed to the 525 points for boys (see bottom panel in Table 2).[21] When we look at the impact of the information treatment on learning outcomes, for boys we find no effect on Spanish test scores, and a moderate and marginally significant increase in math scores (0.24σ). For girls we find a moderate positive effect on scores in Spanish (0.17σ marginally significant at 10% level) and a large (0.34σ) and statistically significant impact on math scores. These impacts translate into a 0.26σ (statistically significant at 5% level) increase in the average score for girls, and 0.15σ statistically not significant increase for boys. We can reject the null hypothesis of no gender-differentiated effect on the average learning score (p-value=0.043)

According to SEP, students are classified in one of the following proficiency levels: a) insufficient, b) regular, c) good, and d) excellent, based on their ENLACE result. About 16% and 30% of the students in our sample taking 9th grade ENLACE were classified as insufficient in Spanish and math respectively. The 9th grade ENLACE proficiency level is a strong predictor of dropping out of upper secondary. In the control group, 40% of students with an insufficient 9th grade ENLACE math were not identified in 12th grade ENLACE, as opposed to 23% among those with a level of regular or more. We study the effect of the information for three different groups: a) those with an insufficient 9th grade ENLACE (henceforth low-ability students) in math, b) those with an ENLACE math score regular or better (henceforth high-ability students), c) those with a missing 9th grade ENLACE score.[22] Results are reported in Panel B in Table 6. The effect on the proxy for probability of finishing upper secondary on time is not statistically different from zero across the three sub-groups. When we look at learning outcomes, we find that among low-ability students, the effect is 0.04σ for Spanish and 0.25σ for math. For both subjects, 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

increases the value of investments that pay out over time.

[21] As shown in Table 1, the gender differences in 9th grade scores observed in our sample are in line with the nation wide difference reported in Table 1.

[22] Table AII displays the balancing properties between treatment and control group in each of the three subgroups. All the results reported in the paper are based on the student 9th grade classification in math, but they do not change when we use Spanish (results available upon request).

the average effect on test score being statistically significant. Nevertheless, when we compare whether the program had a differential effect on the average learning score, we cannot reject that the effect for the low ability is the same as for high ability ones (p-value=0.18) and for missing ability ones (p-value=0.31). In summary, although we find larger coefficients for high-ability students than low-ability ones, we do not have enough statical power to rule out that the effect does not vary with initial level of ability.

We repeat a similar exercise using household income. We define as "high HH income" those students who report a monthly household income in the bracket between $3,501 MX and $7,000 MX or above, while those who report an income in a lower bracket are classified as "low HH income".[23] Results are reported in Panel C in Table 6. Household 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 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%) among high income students, and a 0.18σ increase among missing income students. We can reject the null hypothesis of no differential effect between low and high income students (p-value=0.029), while we can not reject when we compare low income students with those who do not report income information.

In summary, we found larger effects on the learning outcomes of girls than boys, mostly driven by a particularly large impact on the math score. We found no significant evidence of treatment heterogeneity in students' ability, but significant differences associated with household income. The fact that we found an effect only among high income students makes unlikely that the average impacts that we find are driven by the infomation about the PRONABES higher education scholarship. As discussed in section 2.1, PRONABES only targets students with monthly household income below three minimum wages.

4.3 Results on Self-reported Effort

In the simple theoretical framework outlined in section 3.1, information improves student's 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 section 3.3) to provide some preliminary evidence on whether the intervention induced students to work harder. 26% of the boys, as opposed to 18% of the

[23]In 2012, the median price adjusted household income was $4,880 MX.

girls, in the control group report that the statement "I am a person who works hard in school" describes them fully, while for 24% of the boys and 23% of the girls 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 will be viewed favorably by the others. 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 result of the information treatment. In general, self-reported data might capture poorly the actual level of effort. 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. Both correlations are statistically significant at conventional levels (results available upon request).

We use eq. 3 to study 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 7. In column 1 we present the results for the entire sample. Overall the treatment group reports a level of effort that is 0.24σ (statistically significant at 1% 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 column 3 we study how the effect on self-reported effort varies with the level of ability. We do find increases in effort for all three subgroups discussed above (high- and low-ability students and those with no 9th grade ENLACE). The increase among low-ability students is larger in size (0.29σ) than among high-ability students (0.16σ). However, when testing whether the effect varies across the three subgroups, we cannot reject the null hypothesis of no differential effect. In column 4 we show how the effect varies with household income. Both for low and high income students we find large effects of the information package and also in this case we can not reject the null hypothesis of no differential effect.

Although the self-reported nature of the data requires a cautious interpretation of the results presented in this section, the information intervention seems to have improved students' intrinsic motivation, irrespective of their ability level and their income level. 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 that an increase in effort can translate into better learning outcomes only when complemented with other inputs provided at home. An alternative explanation is that only students from relatively well-off backgrounds know how to translate increased effort into better outcomes.

We do find instead that boys and girls respond differentially to the intervention, with the latter reporting higher levels of effort after receiving the information package. Therefore the gender-differentiated effect on learning outcomes documented in section 4.2 can be potentially explained by the differential effect on effort.

5 Further Evidence on the Gender Heterogeneity

The results presented so far show that girls respond to the provision of information by increasing their effort and, as a result, they display a large increase in test scores. For boys, we find instead small and not statistically significant increases in self-reported effort and learning outcomes. In this section we further discuss the differential response of boys and girls, and provide some suggestive evidence on the possible mechanisms behind these differences.

First, we study if both boys and girls update their beliefs in response to the information treatment. For this purpose, we rely on the information elicited as part of the 12th grade *ENLACE de contexto*. Two different types of caveats should be taken into account when comparing the expected earnings collected at the baseline and at the follow-up. As already mentioned, the *ENLACE de contexto* only collects information among 20% 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. 3 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. This might be the result either of the selection into the exam taking, or improved information as students approach the end of high school.

We observe a reduction in the probability of reporting an expected income (oneself) lower than \$4,000 MX among boys and girls in the treatment group, compared to those in the control group. Among girls in the treatment group, we observe an increase in the probability of reporting an expected income between \$4,000 and \$7,000 MX, and no changes in the probability of reporting an expected income above \$7,000. Among boys in the treatment group, we instead observe no change in the probability of reporting an expected income between \$4,000 and \$7,000 MX, but an increase in the probability of reporting an expected income in all the bins above \$7,000 MX. The graphical evidence is supported by the regression results presented in Table 8. 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.

It is puzzling that while both boys and girls update upwards their perceptions regarding the monetary benefits of finishing EMS, only girls report higher effort. We next assess whether more objectives measures of effort support this conclusion. Until 2012, students attending technological EMS schools could choose among three different subtracks: 1) physics and mathematics, 2) economics and accounting, and 3) chemistry and biology.[24] Each subtrack has a large set of optional courses, and among those, students have to choose two (for a total of ten weekly hours) during the last semester of high school. The subtrack of physics and mathematics is the one with the widest choice of math related courses, followed by the economics and accounting, and chemistry and biology.

We compare the school subtrack distribution for boys and girls in treatment and control schools. Results are reported in Table 9. 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%) followed by economics (20%) and chemistry (13%). For girls, the percentage of students who prefer physics and mathematics is 27% and is not statistically different in the treatment and the control group. We do find instead a much larger fraction of girls undertaking economics in the treatment groups (35%) vis-a-vis the control one (19%), with a consequential reduction in the uptake of chemistry and biology. A Kolmogorov Smirnov test allows us to reject the null hypothesis that the subtrack distribution is the same in the treatment and the control group for girls, but we can not reject the null hypothesis for boys. This evidence shows that one of the mechanisms linking the information treatment with improved learning outcomes among

[24]Starting from 2012, as part of a major curriculum reform, students can have a fourth optional subtrack, that covers humanities and social sciences subjects (for details see http://cosdac.sems.gob.mx/riems.php).

girls took place via a change in their subtrack choices. One possible explanation for this result that the available data did not allow us to test, is that our intervention motivated female students to search for more detailed information about the wages related to different careers and, as a result, opted for subtracks with higher expected returns but potentially more demanding. Since 2005 Mexico has a nationwide employment observatory (*Observatorio Laboral* - OLA) that provides updated information on the main labor market outcomes of the different careers - including average wage and gender composition, and it can be easily accessed through a webpage.[25]

It is unclear why boys did not change their behavior, in spite of a more optimistic view about their returns to education. Following our simple conceptual framework, there are two potential explanations: 1) the distance between the perceived returns and the statistic provided as part of the intervention differs for boys and girls; 2) boys and girls have different time preferences.

Only students with expected returns below the statistic provided as part of the intervention should increase effort and improve their results. At the baseline boys and girls do not statistically differ in the probability of reporting an expected earning below the average earning estimated with the ENOE (72% and 70% respectively), and therefore it is unlikely that difference in the baseline perceptions about future earnings can drive the gender differential effect of the information package on proxies for effort, and learning outcomes.

Lower time discount should lead to an increased impact of the program on effort. There is increasing evidence that men and women differ in time discount.[26] 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, we find that 20% of boys, as opposed to 15% of girls, would prefer accepting \$3,000 MX today, regardless of the amount offered in one year time. We define these individuals as the "high time discount" students, and "low time discount" as all students willing to give up the \$3,000 MX today in exchange for a larger sum in the future. We study whether the treatment effect

[25]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 \$8,617 MX per month and 87% 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% and 46.4% of the total employees respectively. Careers such as engineering, that are common outcomes for those taking the physics and mathematics subtrack, feature on average the highest wages but an extremely low proportion of women. The average wages for a mining engineer and an automotive one are \$19,838 MX and \$14,036 MX per month respectively, but the percentage of women employed are 11.4% and 1.3%, respectively.

[26]See, among others, Dittrich and Leipold (2014) and Bauer et al. (2012). For Mexico, Rubalcava et al. (2009), using direct evidence on time preference from the Mexican Family Life Survey, finds that women have lower time discount than men.

varies with proxies for time discount. The evidence presented in column 1 in Table 10 shows that low time discount students display a very large and significant increase 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 10), but we can not reject the null hypothesis of no differential effect.

In summary, both boys and girls update their priors about the labor market returns to education, but only the latter exert more effort, partly by choosing subtracks with higher mathematical content. We provide some suggestive evidence that part of the difference might be explained by gender differences in time preferences. However, 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.

There might be alternative explanations behind the gender-specific response to the information treatment. 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. Parents might invest more in girls if they were underestimating their future labor market returns.[27] Similarly, teachers in treatment schools 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 Table 11 shows no effect of the program on students' perceptions about teacher practices and parental involvement, either for boys or girls.

One conjecture behind the gender-specific effect of the intervention is that, ex-ante, boys might have had a lower scope for improving their effort through the subtrack choice. The fact that in the control group almost half of the boys, as opposed to 26% of the women, were opting for the most difficult subtrack, and they have math results 0.4σ higher than girls - while girls were doing better than boys in 9th grade - is suggestive that, at least in our sample, boys are already exerting a higher level of effort compared to girls, at least regarding math. This difference might be either the result of different preferences - for instance boys are less risk averse than girls (Charness and Gneezy 2012) and they are willing to attend more

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

difficult subtracks - or social norms. On the one hand, irrespective of how well informed they are, boys who decide to attend a technological high school are expected to choose careers that require high mathematical competence (e.g. engineering), and they might internalize these expectations by increasing their level of effort in math-related subjects. On the other hand, it has been shown for Mexico 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 difficult subtracks. The information intervention might have helped girls not only to improve their level of awareness, but also to give more salience to the labor market returns when deciding the optimal level of effort in school.

6 Conclusions and Policy Recommendations

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 the context of a developing country. We study the impact of an intervention that targets 10th grade students in Mexico and provides them information about the returns to upper secondary and tertiary education, as well as a source of financial aid for tertiary education and life expectancy. The *Percepciones* pilot displayed no impact on the probability of on-time high school graduation. This can be explained, at least partly, by the fact that the information intervention seems to have a larger impact among students who display a minimum level of socioeconomic conditions, that most high school dropouts miss.

The intervention had a sizeable positive effect on learning outcomes, with the average of the standardized scores in math and Spanish increasing by 0.2 standard deviations. The intervention had a very heterogeneous impact. Almost three years after being exposed to the treatment, girls who received the intervention experienced a large increase in their scores, especially the math one. Similarly, we find that students with relatively better socioeconomic conditions display significantly higher impacts.

Both boys and girls in the treatment group update their beliefs about the returns to education, but only the latter report increased effort and switch to more demanding and math-intensive subtracks. Although our study was not designed to analyze a gender differential impact, the available data do allow to test whether some of the mechanisms previously mentioned by the literature can operate in our context. Initial level of information and potential gender biased behaviors of parents and teachers do not seem to play any role in explaining our results. Differences in time preferences can explain very little, if anything, of the gender differentiated effect of the intervention.

The results presented in this paper also show that a pure informational treatment is not an effective strategy to reduce upper secondary dropout rates in Mexico and are not able to improve learning outcomes among students from disadvantaged backgrounds, since the increase in effort has to be complemented by other inputs. However, given the large effect on math test scores for girls and high-ability students, as well as the virtually zero cost of the intervention, the results presented in this study support previous findings showing the cost-effectiveness of information interventions. For many adolescent girls in Mexico, information could be enough to help them visualize a future different from the traditional stereotypes, and base their present schooling decisions and efforts on their potential labor market implications.

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Figure 1: Timeline of the *Percepciones* Project

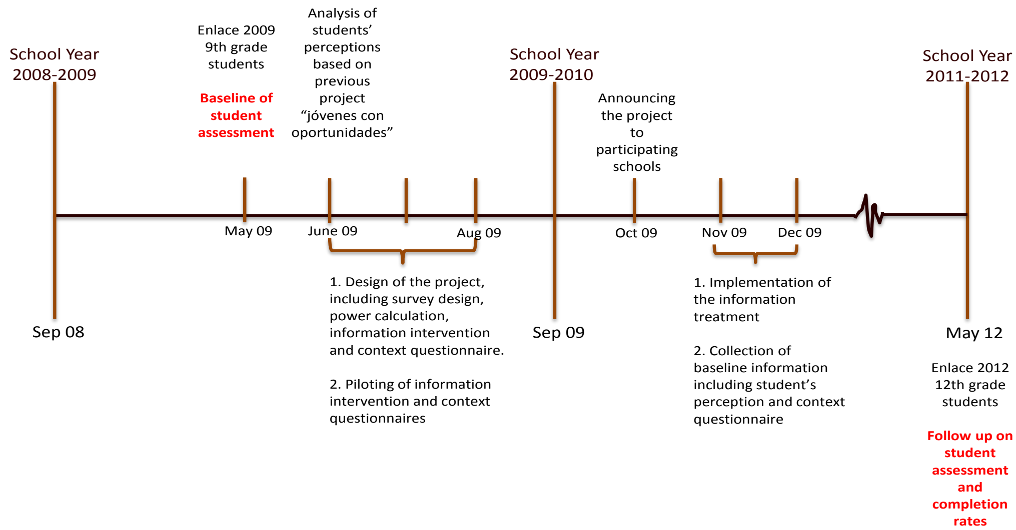


Figure 2: Baseline Monthly Expected Earnings (Self) upon finishing Upper Secondary

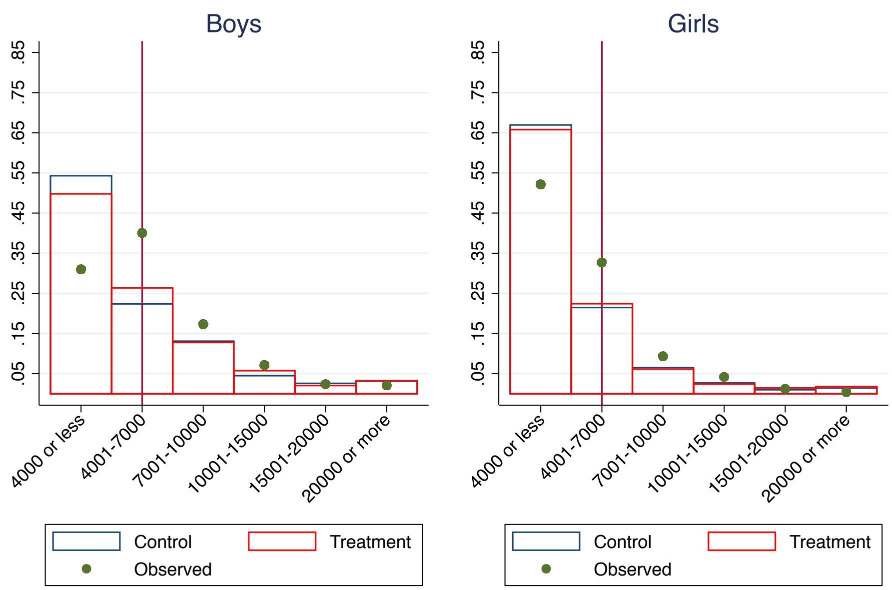
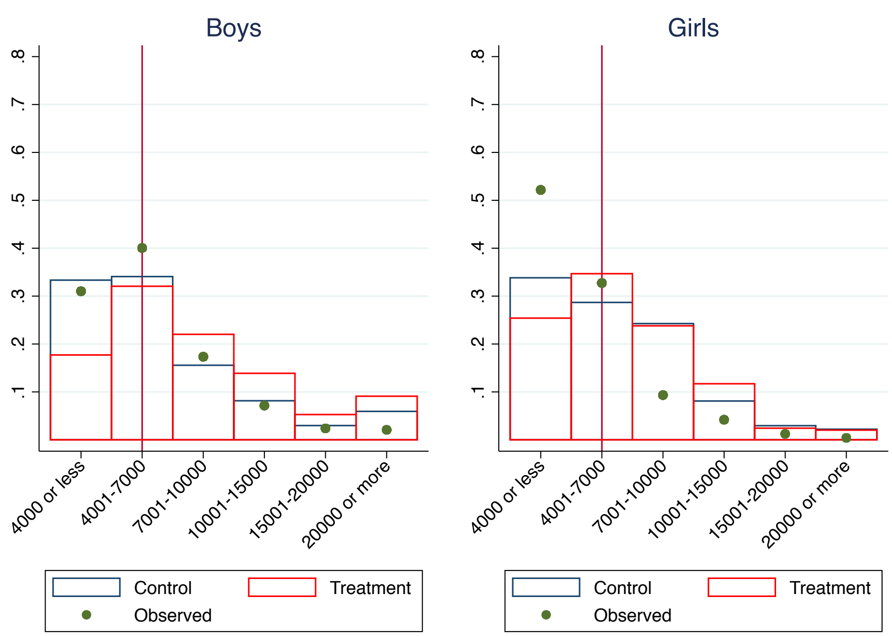


Figure 3: Follow-up Monthly Expected Earnings (Self) upon finishing Upper Secondary



Note: The red 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 observed distribution is based on data from ENOE second quarter of 2009. The baseline expected earnings for themselves upon finishing upper secondary 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.

Table 1: Evolution of Gender Differences in Learning in Mexico

	Boys	Girls	Total	Observations
		ENLACE 6th Grade		
Spanish	497.115	528.142	512.425	1,985,852
	(104.940)	(102.914)	(105.097)	
Math	505.488	522.422	513.844	1,985,852
	(112.061)	(108.299)	(110.545)	
		ENLACE 9th Grade		
Spanish	491.835	523.131	507.953	1,389,773
	(103.799)	(102.705)	(104.415)	
Math	520.628	529.398	525.145	1,389,773
	(113.688)	(105.173)	(109.473)	
		ENLACE 12th Grade		
Spanish	498.914	523.697	512.379	630,311
	(96.632)	(88.927)	(93.345)	
Math	600.302	570.487	584.103	629,975
	(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).

Table 2: Baseline characteristics, by Treatment status

	Full Sample			Boys			Girls		
	T	C	p-value T=C	T	C	p-value T=C	T	C	p-value T=C
				Panel A: Survey variables					
Age	16.5	16.5	0.940	16.6	16.6	0.778	16.4	16.4	0.866
	(0.932)	(0.788)		(0.982)	(0.882)		(0.868)	(0.662)	
People in the hh	5.16	5.23	0.526	5.17	5.2	0.736	5.16	5.27	0.421
	(1.74)	(1.76)		(1.75)	(1.64)		(1.74)	(1.87)	
Father works	0.944	0.932	0.206	0.958	0.931	0.001	0.927	0.934	0.648
	(0.231)	(0.252)		(0.2)	(0.254)		(0.261)	(0.249)	
Mom works	0.493	0.459	0.234	0.472	0.445	0.479	0.516	0.473	0.126
	(0.5)	(0.498)		(0.499)	(0.497)		(0.5)	(0.5)	
Father with primary	0.286	0.319	0.448	0.26	0.298	0.432	0.314	0.342	0.554
	(0.452)	(0.466)		(0.439)	(0.458)		(0.464)	(0.475)	
Mother with primary	0.303	0.342	0.357	0.282	0.329	0.308	0.326	0.354	0.474
	(0.46)	(0.474)		(0.45)	(0.47)		(0.469)	(0.479)	
Father with secondary	0.363	0.369	0.813	0.367	0.371	0.844	0.358	0.366	0.835
	(0.481)	(0.483)		(0.482)	(0.483)		(0.48)	(0.482)	
Mother with secondary	0.392	0.416	0.283	0.396	0.403	0.684	0.388	0.43	0.191
	(0.488)	(0.493)		(0.489)	(0.491)		(0.488)	(0.495)	
Father with hs or higher	0.351	0.312	0.338	0.372	0.331	0.338	0.328	0.292	0.410
	(0.478)	(0.463)		(0.484)	(0.471)		(0.47)	(0.455)	
Mother with hs or higher	0.305	0.242	0.118	0.322	0.268	0.187	0.286	0.216	0.115
	(0.46)	(0.428)		(0.468)	(0.443)		(0.452)	(0.411)	
Heater at Home	0.663	0.598	0.333	0.701	0.596	0.145	0.622	0.601	0.706
	(0.473)	(0.49)		(0.458)	(0.491)		(0.485)	(0.49)	
Washing Machine	0.795	0.778	0.677	0.824	0.798	0.484	0.764	0.758	0.877
	(0.403)	(0.416)		(0.381)	(0.402)		(0.425)	(0.429)	
PC at Home	0.605	0.521	0.122	0.632	0.551	0.125	0.576	0.49	0.154
	(0.489)	(0.5)		(0.482)	(0.498)		(0.494)	(0.5)	
Internet at Home	0.443	0.354	0.142	0.46	0.382	0.201	0.425	0.325	0.125
	(0.497)	(0.478)		(0.499)	(0.486)		(0.495)	(0.469)	
Hours for homeworks	5.5	5.37	0.641	5.58	5.62	1.000	5.41	5.11	0.357
	(5.89)	(5.64)		(6.2)	(6.23)		(5.53)	(4.95)	
School days missed	2.58	2.79	0.158	2.7	2.8	0.644	2.45	2.78	0.132
	(2.3)	(2.41)		(2.39)	(2.42)		(2.2)	(2.41)	
Sec. school qualification	8.52	8.44	0.326	8.37	8.24	0.120	8.68	8.65	0.698
	(0.812)	(0.82)		(0.817)	(0.803)		(0.776)	(0.786)	
Failed subject in sec.	0.229	0.243	0.569	0.287	0.297	0.810	0.165	0.188	0.331
	(0.42)	(0.429)		(0.452)	(0.457)		(0.372)	(0.391)	
				Panel B: 9th grade ENLACE results					
Missing ENLACE	0.216	0.282	0.071	0.241	0.292	0.181	0.188	0.271	0.054
	(0.411)	(0.45)		(0.428)	(0.455)		(0.391)	(0.445)	
Spanish Score	533	524	0.522	517	507	0.404	549	542	0.680
	(98.8)	(96.5)		(97.4)	(96.9)		(97.8)	(92.8)	
Insufficient in Spanish	0.205	0.195	0.739	0.236	0.237	0.954	0.171	0.152	0.504
	(0.404)	(0.397)		(0.425)	(0.426)		(0.377)	(0.359)	
Math Score	542	529	0.343	538	525	0.365	546	533	0.380
	(104)	(97.4)		(104)	(99)		(104)	(95.6)	
Insufficient in Math	0.362	0.359	0.933	0.359	0.364	0.895	0.364	0.353	0.796
	(0.481)	(0.48)		(0.48)	(0.481)		(0.481)	(0.478)	

Note: We report the mean of each variable, and its standard deviation in parentheses. 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 3: Baseline Perceptions about Earnings, by Treatment Status

	Full Sample			Boys			Girls		
	T	C	p-value T=C	T	C	p-value T=C	T	C	p-value T=C
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expected Earnings (Self) Lower Sec	2559	2536	0.649	2958	2923	0.582	2125	2139	0.708
	(2509)	(2421)		(2880)	(2757)		(1940)	(1942)	
Expected Earnings (Self) Upper Sec	5082	4828	0.735	5830	5531	0.944	4260	4101	0.792
	(4853)	(4419)		(5384)	(5027)		(4039)	(3546)	
Expected Earnings (Self) University	12060	11492	0.721	13296	12051	0.349	10718	10916	0.665
	(11469)	(11090)		(11727)	(10387)		(11036)	(11751)	
Implied Expected Return (Self) Upper Sec	2355	2256	0.892	2720	2520	0.718	1954	1987	0.612
	(2904)	(2802)		(3243)	(3032)		(2419)	(2518)	
Implied Expected Return (Self) University	9695	9124	0.642	10818	9366	0.256	8453	8875	0.507
	(11852)	(11266)		(13089)	(10688)		(10181)	(11831)	
Expected Earnings (Average) Lower Sec	1962	1902	0.800	2252	2227	0.740	1642	1567	0.533
	(1675)	(1641)		(1897)	(1856)		(1318)	(1305)	
Expected Earnings (Average) Upper Sec	4033	3726	0.314	4649	4282	0.440	3351	3154	0.454
	(3445)	(3197)		(3756)	(3436)		(2921)	(2821)	
Expected Earnings (Average) University	11534	10663	0.354	12899	11699	0.328	10020	9590	0.714
	(11224)	(10782)		(11983)	(10977)		(10114)	(10477)	
Implied Expected Return (Average) Upper-Sec	2004	1817	0.261	2348	2058	0.188	1632	1569	0.680
	(2359)	(2152)		(2601)	(2250)		(2000)	(2018)	
Implied Expected Return (Average) University	9296	8506	0.309	10477	9223	0.209	8014	7770	0.804
	(10505)	(10002)		(11298)	(10037)		(9412)	(9919)	

Note: We report the mean of each variable expressed in $ MX, and its standard deviation in parentheses. 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 1% and the bottom 1% of the expected earnings distribution have been trimmed. When using *Self* we refer to the earning that the respondent expects for herself/himself when aged between 30 and 40. When using *Average* we refer to the earning that the respondent expects for the average person when aged between 30 and 40.
The statistics provided to the male and female respondents are described in section 2.1.

Table 4: Correlation between Baseline Expectations and Student Outcomes in 12th Grade

	Has ENLACE 12th grade				Spanish				Math			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Expected Earnings (Self) Upper-Sec	0.003				0.115***				0.121***			
	(0.014)				(0.039)				(0.037)			
Log Expected Earnings (Self) University		0.013				0.143***				0.100***		
		(0.014)				(0.037)				(0.035)		
Log Expected Earnings (Average) Upper-Sec			0.005				0.062				0.076**	
			(0.015)				(0.040)				(0.039)	
Log Expected Earnings (Average) University				0.020				0.067*				0.043
				(0.013)				(0.035)				(0.034)
Observations	1436	1434	1436	1436	915	913	915	915	915	913	915	915
R^2	.0473	.0488	.0473	.0488	.0572	.0633	.0506	.052	.104	.102	.0974	.0952

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. Has ENLACE 12th grade 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. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 5: Full Sample

Outcome Variable	(1) ENLACE (Y/N)	(2)	(3) Spanish	(4)	(5) Math	(6)	(7) Average Score	(8)
Treatment	0.025	0.004	0.161	0.107	0.322*	0.285**	0.242*	0.198*
	(0.042)	(0.029)	(0.134)	(0.096)	(0.170)	(0.140)	(0.139)	(0.104)
Strata Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4145	4131	2531	2520	2531	2520	2531	2520
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. Strata dummies are the dummies for the 3 macro regions (North, Center, South) that is the level at which the randomization has been stratified. Controls include age, a dummy for gender, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), dummies for the level of proficiency in math and Spanish in the 9th grade ENLACE, and dummies for whether the 9th grade score in math and Spanish are missing, dummies for whether the mother and the father work, dummies for whether the information on father's and mother's work status are missing, dummies to proxy for the presence PC and internet at home. Has ENLACE 12th grade 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. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 6: Treatment Heterogeneity

	(1)	(2)	(3)	(4)
Outcome Variable	Took ENLACE 12th grade (Y/N)	Spanish	Math	Average Score
	Panel A Heterogeneity by Gender			
Treat X Male	-0.001	0.059	0.237*	0.151
	(0.032)	(0.105)	(0.139)	(0.108)
Treat X Female	0.011	0.167*	0.338**	0.255**
	(0.034)	(0.093)	(0.144)	(0.104)
Strata Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	4131	2520	2520	2520
P-Value H_0: Boys=Girls	0.693	0.098	0.102	0.043
	Panel B Heterogeneity by Ability			
Treatment X Low Ability	-0.018	0.039	0.246	0.146
	(0.043)	(0.117)	(0.169)	(0.127)
Treatment X High Ability	0.022	0.152	0.333***	0.241**
	(0.027)	(0.098)	(0.129)	(0.102)
Treatment X Missing Ability	0.006	0.141	0.365*	0.263
	(0.044)	(0.182)	(0.188)	(0.167)
Strata Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	4131	2520	2520	2520
P-Value H_0: Low Ability=High Ability	0.261	0.161	0.314	0.180
P-Value H_0: Low Ability=Missing	0.598	0.459	0.276	0.309
	Panel C Heterogeneity by HH Income			
Treatment X Low Income	0.011	0.046	0.198	0.124
	(0.035)	(0.098)	(0.148)	(0.107)
Treatment X High Income	-0.005	0.178*	0.322**	0.253**
	(0.029)	(0.104)	(0.135)	(0.105)
Treatment X Missing Income	0.019	-0.030	0.379**	0.179
	(0.043)	(0.131)	(0.184)	(0.143)
Strata Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	4131	2520	2520	2520
P-Value H_0: Low Income=High Income	0.493	0.064	0.060	0.029
P-Value H_0: Low Income=Missing	0.859	0.470	0.143	0.592

Note: Robust standard errors clustered at school level in parentheses. Strata dummies are the dummies for the 3 macro regions (North, Center, South) that is the level at which the randomization has been stratified. Controls include age, a dummy for gender, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), dummies for the level of proficiency in math and Spanish in the 9th grade ENLACE, and dummies for whether the 9th grade score in math and Spanish are missing, dummies for whether the mother and the father work, dummies for whether the information on father's and mother's work status are missing, dummies to proxy for the presence PC and internet at home. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 7: Impact on Self-reported Effort

	(1) Full Sample	(2) Gender	(3) Ability	(4) HH Income
Treat	0.240***			
	(0.027)			
Treat X Male		0.110		
		(0.094)		
Treat X Female		0.349***		
		(0.060)		
Treat X Low Ability			0.297 ***	
			(0.080)	
Treat X High Ability			0.156*	
			(0.082)	
Treat X Missing Ability			0.194	
			(0.161)	
Treat X Low Income				0.222 ***
				(0.078)
Treat X High Income				0.303 ***
				(0.071)
Treat X Missing Income				0.054
				(0.174)
Strata Dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	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 Ability=High Ability			0.359	
P-Value H_0: Low Ability=Missing			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. Strata dummies are the dummies for the 3 macro regions (North, Center, South) that is the level at which the randomization has been stratified.Strata dummies are the dummies for the 3 macro regions (North, Center, South) that is the level at which the randomization has been stratified. Controls include age, a dummy for gender, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), dummies for the level of proficiency in math and Spanish in the 9th grade ENLACE, and dummies for whether the 9th grade score in math and Spanish are missing, dummies for whether the mother and the father work, dummies for whether the information on father's and mother's work status are missing, dummies to proxy for the presence PC and internet at home. 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.

Table 8: Effect on Perceived Earnings

	(1) Less than 4,000	(2) Between 4,000 and 7,000	(3) Above 7,000
Treat X Male	-0.171***	0.005	0.155 ***
	(0.051)	(0.034)	(0.047)
Treat X Female	-0.102	0.072 ***	0.023
	(0.067)	(0.023)	(0.054)
Strata Dummies	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	726	726	726
Mean Dep. Control Group	0.338	0.287	0.375
SD Dep. Control Group	0.475	0.454	0.486
P-Value H_0: Boys=Girls	0.163	0.103	0.018

Note: Robust standard errors clustered at school level in parentheses. Strata dummies are the dummies for the 3 macro regions (North, Center, South) that is the level at which the randomization has been stratified. Controls include age, a dummy for gender, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), dummies for the level of proficiency in math and Spanish in the 9th grade ENLACE, and dummies for whether the 9th grade score in math and Spanish are missing, dummies for whether the mother and the father work, dummies for whether the information on father's and mother's work status are missing, dummies to proxy for the presence PC and internet at home. The dummy *Less than $4,000 MX* takes the value 1 for an expected monthly earning below $4,000 MX upon finishing upper secondary, 0 otherwise. The dummy *Between $4,000 MX and $7,000 MX* takes the value 1 for an expected monthly earning between $4,000 MX and $7,000 MX upon finishing upper secondary, 0 otherwise. The dummy *More than $7,000 MX* takes the value 1 for an expected earning above $7,000 MX upon finishing upper secondary, 0 otherwise. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 9: Subtrack Distribution

	Boys			Girls		
	Control (1)	Treatment (2)	Total (3)	Control (4)	Treatment (5)	Total (6)
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 Administration	16.42%	22.22%	19.94%	18.66%	35.39%	29.44%
Observations	134	207	341	134	243	377
	K-S Test=0.059		p-value = 0.95	K-S Test=0.167		p-value = 0.016

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

Table 10: Understanding Gender Differences: the Role of Time Preferences

	(1) Self-Reported Effort Full Sample	(2) Average Score Full Sample
Treat X High Discount	0.011	0.140
	(0.125)	(0.113)
Treat X Low Discount	0.277***	0.204*
	(0.033)	(0.107)
Strata Dummies	Yes	Yes
Controls	Yes	Yes
Observations	713	2500
Proportion of girls with High Discount	0.148	
Proportion of boys with High Discount	0.195	
P-Value H_0 Low Discount=High Discount	0.054	0.354

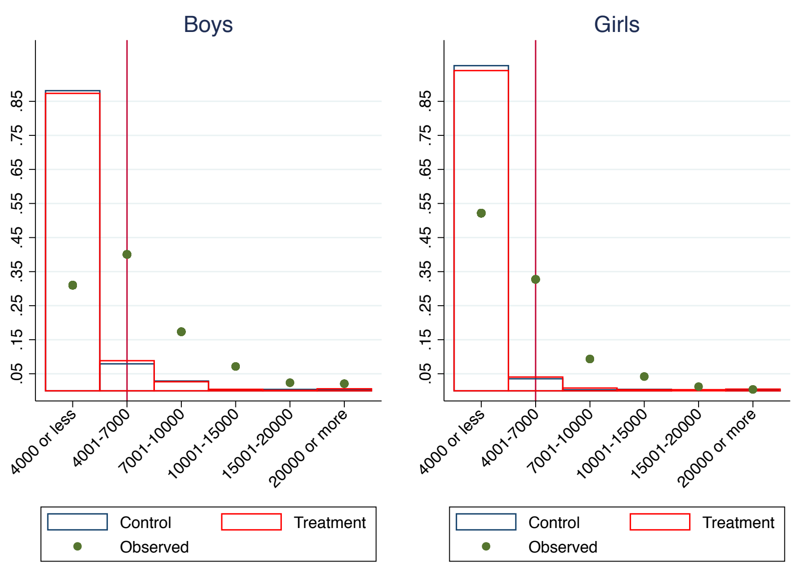
Note: Robust standard errors clustered at school level in parentheses. Strata dummies are the dummies for the 3 macro regions (North, Center, South) that is the level at which the randomization has been stratified.Strata dummies are the dummies for the 3 macro regions (North, Center, South) that is the level at which the randomization has been stratified. Controls include age, a dummy for gender, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), dummies for the level of proficiency in math and Spanish in the 9th grade ENLACE, and dummies for whether the 9th grade score in math and Spanish are missing, dummies for whether the mother and the father work, dummies for whether the information on father's and mother's work status are missing, dummies to proxy for the presence PC and internet at home. The dummy *Low Time Discount* takes the value 1 if the respondent would be willing to renounce $3,000 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.

Table 11: Additional Explanations for the Gender Differential: Teacher and Parental Behaviour

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
Treat X Male	0.003	0.050	0.071	-0.036	0.009	-0.039
	(0.043)	(0.042)	(0.045)	(0.039)	(0.036)	(0.047)
Treat X Female	-0.003	-0.093	-0.061	0.004	-0.053	-0.054
	(0.043)	(0.074)	(0.063)	(0.020)	(0.034)	(0.046)
Strata Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	727	727	725	728	728	727
Mean Dep. Control Group for Girls	0.846	0.723	0.346	0.759	0.847	0.569
Mean Dep. Control Group for Boys	0.860	0.691	0.331	0.765	0.846	0.593
P-Value H_0: Girls=Boys	0.845	0.119	0.158	0.340	0.178	0.829

Note: Robust standard errors clustered at school level in parentheses. Strata dummies are the dummies for the 3 macro regions (North, Center, South) that is the level at which the randomization has been stratified.Strata dummies are the dummies for the 3 macro regions (North, Center, South) that is the level at which the randomization has been stratified. Controls include age, a dummy for gender, dummies for the type of specialization of the school (industrial, agricultural, or ocean-related), dummies for the level of proficiency in math and Spanish in the 9th grade ENLACE, and dummies for whether the 9th grade score in math and Spanish are missing, dummies for whether the mother and the father work, dummies for whether the information on father's and mother's work status are missing, dummies to proxy for the presence PC and internet at home. 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 *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Figure AI: Baseline Monthly Expected Earnings (Average) upon finishing Upper Secondary



Note: The red 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 observed distribution is based on data from the ENOE second quarter of 2009. The baseline expected earnings for the average person upon finishing upper secondary were elicited as part of the baseline survey conducted in November 2009.

Table AI: Comparing Characteristics of Matched and Unmatched Observations

	Matched	Unmatched	p-value M=U
	(1)	(2)	(3)
Age	16.4	16.7	0.000
	(0.665)	(1.27)	
People in the hh	5.17	5.3	0.033
	(1.74)	(1.78)	
Father works	0.934	0.949	0.110
	(0.248)	(0.221)	
Mother works	0.482	0.457	0.229
	(0.5)	(0.498)	
Father with primary	0.302	0.305	0.917
	(0.459)	(0.461)	
Mother with primary	0.319	0.334	0.502
	(0.466)	(0.472)	
Father with secondary	0.36	0.385	0.354
	(0.48)	(0.487)	
Mother with secondary	0.394	0.435	0.108
	(0.489)	(0.496)	
Father with hs or higher	0.338	0.31	0.194
	(0.473)	(0.463)	
Mother with hs or higher	0.287	0.231	0.005
	(0.453)	(0.422)	
Heater at Home	0.638	0.609	0.352
	(0.481)	(0.488)	
Washing Machine	0.79	0.778	0.581
	(0.408)	(0.416)	
PC at Home	0.577	0.522	0.029
	(0.494)	(0.5)	
Internet at Home	0.417	0.344	0.003
	(0.493)	(0.475)	
Hours for homeworks	5.49	5.26	0.305
	(5.86)	(5.48)	
School days missed	2.68	2.72	0.755
	(2.36)	(2.36)	
Sec. school qualification	8.51	8.38	0.003
	(0.82)	(0.801)	
Failed subject	0.223	0.227	0.004
	(0.416)	(0.448)	

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 AII: Covariates Balance for different levels of ability

	Math 9th Insuff			Math 9th Suff or more			Math 9th Missing		
	T	C	p-value T=C	T	C	p-value T=C	T	C	p-value T=C
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: Survey Variables					
Age	16.5	16.5	0.765	16.4	16.3	0.861	16.8	16.7	0.573
	(0.721)	(0.705)		(0.6)	(0.617)		(1.53)	(1.01)	
People in the hh	5.28	5.3	0.636	5	5.12	0.620	5.28	5.31	0.631
	(1.92)	(1.94)		(1.51)	(1.56)		(1.83)	(1.74)	
Father works	0.942	0.926	0.196	0.942	0.925	0.230	0.949	0.948	0.877
	(0.234)	(0.262)		(0.234)	(0.264)		(0.22)	(0.222)	
Mother works	0.49	0.482	0.857	0.495	0.459	0.341	0.495	0.429	0.120
	(0.5)	(0.5)		(0.5)	(0.499)		(0.501)	(0.495)	
Father with primary	0.333	0.349	0.746	0.243	0.295	0.384	0.292	0.315	0.354
	(0.472)	(0.477)		(0.429)	(0.456)		(0.455)	(0.465)	
Mother with primary	0.338	0.367	0.531	0.265	0.314	0.424	0.32	0.345	0.355
	(0.473)	(0.482)		(0.442)	(0.464)		(0.467)	(0.476)	
Father with secondary	0.383	0.369	0.747	0.348	0.341	0.796	0.359	0.403	0.507
	(0.486)	(0.483)		(0.477)	(0.475)		(0.48)	(0.491)	
Mother with secondary	0.409	0.39	0.742	0.373	0.408	0.240	0.401	0.46	0.226
	(0.492)	(0.488)		(0.484)	(0.492)		(0.491)	(0.499)	
Father with hs or higher	0.284	0.282	0.919	0.409	0.364	0.508	0.349	0.282	0.098
	(0.451)	(0.45)		(0.492)	(0.481)		(0.477)	(0.45)	
Mother with hs or higher	0.253	0.243	0.668	0.362	0.278	0.206	0.278	0.195	0.012
	(0.435)	(0.429)		(0.481)	(0.448)		(0.449)	(0.396)	
Heater at Home	0.639	0.577	0.539	0.704	0.621	0.181	0.626	0.597	0.437
	(0.481)	(0.494)		(0.457)	(0.485)		(0.485)	(0.491)	
Washing Machine	0.77	0.766	0.946	0.825	0.791	0.645	0.78	0.776	0.624
	(0.421)	(0.423)		(0.38)	(0.407)		(0.415)	(0.417)	
PC at Home	0.528	0.487	0.530	0.676	0.598	0.252	0.596	0.465	0.029
	(0.5)	(0.5)		(0.468)	(0.491)		(0.491)	(0.499)	
Internet at Home	0.369	0.35	0.737	0.512	0.419	0.285	0.432	0.276	0.006
	(0.483)	(0.477)		(0.5)	(0.494)		(0.496)	(0.447)	
Hours for homeworks	5.44	5.33	0.995	5.52	5.68	0.997	5.56	5.03	0.283
	(6.47)	(6.13)		(5.25)	(5.62)		(6.08)	(4.98)	
School days missed	2.89	3.08	0.435	2.13	2.51	0.044	2.75	2.69	0.727
	(2.57)	(2.67)		(1.74)	(2.16)		(2.48)	(2.27)	
Sec. school qualification	8.27	8.21	0.296	8.79	8.72	0.627	8.42	8.36	0.308
	(0.768)	(0.769)		(0.763)	(0.812)		(0.82)	(0.785)	
Failed subject in sec.	0.293	0.277	0.676	0.159	0.173	0.758	0.258	0.291	0.265
	(0.455)	(0.448)		(0.366)	(0.379)		(0.438)	(0.455)	

Note: We report the mean of each variable, and its standard deviation in parentheses. 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.