Understanding the Income Gradient in College Attendance in Mexico: The Role of Heterogeneity in Expected Returns to College

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Abstract

This paper studies the determinants of college attendance in Mexico. I use subjective quantitative expectations of future earnings to analyze both the causes and the implications of the steep income gradient in higher-education enrollment. In particular, I examine whether data on individuals' expected returns to college as well as on their perceived earnings risk can improve our understanding of heterogeneity in college attendance choices. I find that while expected returns and perceived risk from human capital investment are important determinants, lower returns or higher risk are not sufficient, alone, to explain the poor's low attendance rates. I also find that poor individuals require significantly higher expected returns to be induced to attend college, implying that they face significantly higher costs than individuals with wealthy parents. I then test predictions of a simple model of college attendance choice in the presence of credit constraints, using parental income and wealth as a proxy for the household's (unobserved) interest rate. I find that poor individuals with high expected returns are particularly responsive to changes in direct costs such as tuition, which is consistent with credit constraints playing an important role. To evaluate potential welfare implications of introducing a means-tested student loan program, I apply the Local Instrumental Variables approach of Heckman and Vytlacil (2005) to my model of college attendance choice. I find that a sizeable fraction of poor individuals would change their decision in response to a reduction in the interest rate, and that the individuals at the margin have higher expected returns than the individuals already attending college. This suggests that policies such as governmental student loan programs could lead to large welfare gains.

JEL-Classification: I21, I22, I38, O15, O16

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1 Introduction

In both developed and developing countries there is a strong association between children's college attendance rates and parental income. For example, in the U.S. the poorest 40% of the relevant age group (18 to 24 years old) represent around 20% of the student body, while the richest 20% constitute 45%. For Mexico, the country I will be studying in this paper, the poorest 40% represent only 8% of the student body, which is low even compared to other Latin American countries, while the richest 20% constitute 60% of the student body. In addition overall college enrollment is particularly low in Mexico.[1] In this paper I use subjective quantitative expectations of future earnings to analyze both the causes and the implications of the steep income gradient in college attendance. In particular, I examine whether data on individuals' expected returns to college as well as on their perceived risk from human capital investment can improve our understanding of heterogeneity in college attendance decisions.

A traditional explanation for the income gradient in college attendance is credit constraints. Suppose that credit markets are imperfect in that banks only lend to individuals with collateral. Since college attendance involves direct costs (such as tuition), individuals from poor families, unable to cover such costs with parental income or with borrowed funds due to lack of collateral, will choose not to attend college even in the presence of high expected returns.[2]

An alternative explanation for the gradient is that it may be optimal for poor individuals not to attend college even if they could borrow to finance higher education because of low expected returns from human capital investment. Several papers in the literature, such as Cameron and Heckman (1998, 2001) and Carneiro and Heckman (2002), attribute differences in college attendance rates between poor and rich in the US to differences in "college readiness". As stated in Carneiro and Heckman (2002), "most of the family income gap in enrollment is due to long-run factors that produce abilities needed to benefit from participation in college." They disprove the importance of credit constraints in the U.S. by showing that once one controls for ability and parental background measures (which proxy for returns to college and preferences), parental income at the time of college attendance ceases to have a significant effect on college attendance. I cannot show this in my data. Nevertheless, it would be premature to conclude that this proves the importance of credit constraints.

[1] A strong correlation between children's educational attainment and parental resources is well-documented for most countries, see e.g. the cross-country overview of Blossfeldt and Shavit (1993). The correlation is particularly strong for developing countries, see e.g. Behrman, Gaviria and Szekely (2002) for the case of Latin America. See Table 1 in which I compare several Latin American countries (and the US and an OECD average) in terms of attendance rates, inequality in access to higher education, and availability of fellowship and student loan programs.

[2] Conventionally, an individual is defined as credit constrained if she would be willing to write a contract in which she could credibly commit to paying back the loan ("enslave herself in the case of default") taking into account the riskiness of future income streams and of default. But because such contracts are illegal, banks may choose to lend only to individuals who offer collateral to be seized in case of default.

Consider the conventional model of educational choices under uncertainty. In such a model, the college attendance choice depends on expected returns and risk from investing in college education, preferences, and potential credit constraints. The identification challenge is that all these determinants are typically unobserved by the econometrician (see, e.g., Manski (2004) and Cunha and Heckman (2007)). This paper aims at improving our understanding of college attendance decisions and contributing to the debate about the causes of the steep income gradient by making use of a particularly suitable data set containing information on individuals' subjective expectations of earnings and perceived earnings risk.

The existing literature derives measures of earnings expectations using earnings realizations. This approach has at least two problems. First, one has to make assumptions about the individual's information set as well as the mechanisms behind expectation formation. These assumptions include whether earnings shocks were anticipated at the time of the choice (which is particularly problematic if large and unpredictable earnings shocks are the norm, as they are in developing countries) and whether people have precise information about their own ability. Second, computing expected returns to college requires constructing expected earnings in a counterfactual state. Thus, researchers have to make assumptions about how individuals form these expectations, i.e. whether and how they solve the problem that the observed earnings are from individuals who have self-selected into schooling. Another potentially important determinant of college attendance is perceived earnings risk. Taking into account earnings risk is relevant for the credit constraints issue, as it might not be optimal for poor individuals to attend college, despite high expected returns, if they face particularly risky college earnings.[3] Most papers in the literature neglect the importance of risk as a determinant of educational choice and assume no uncertainty or certainty equivalence (see, e.g., Cameron and Taber (2004) and Carneiro, Heckman and Vytlacil (2005)).

If there are differences in expected returns or perceived earnings risk, which are correlated with parental income, this could lead to a spurious positive correlation between parental income and college attendance. Having data on each individual's distribution of future earnings for both college attendance states enables me to address this concern directly. Since what matters for the college attendance decision is each individual's perception of her own skills and how these skills affect her future earnings, these data ideally provide respondent's earnings expectations and perceptions of earnings risk conditional on their information sets at the time of the decision.

One of the paper's main findings is that expected returns to college and perceived risk of future earnings are important determinants of college attendance decisions, but that lower returns or higher risk are not sufficient to explain the poor's low college attendance rates. I also find that poor individuals require significantly higher expected returns to be induced to attend college, implying

[3] Papers that take into account this determinant include Padula and Pistaferri (2001) and Belzil and Hansen (2002). Only the former paper employs subjective expectations but aggregates perceived employment risk for education groups to analyze whether the implicit return to education is underestimated when not taking into account effects of different schooling levels on later earnings and employment risk.

that they face significantly higher costs than individuals with wealthy parents. To understand the role of different cost components, I test predictions of a simple model of college attendance choice in the presence of credit constraints, using parental income and wealth as proxies for the unobserved household's interest rate. I find that poor individuals with high expected returns are particularly responsive to changes in direct costs such as tuition, which is consistent with credit constraints playing an important role. To evaluate potential welfare implications of introducing a means-tested student loan program, I apply the Local Instrumental Variables (LIV) approach of Heckman and Vytlacil (2005) to my model of college attendance choice making use of subjective expectations. I find that a sizeable fraction of poor individuals would change their decision in response to a reduction in the interest rate, and that the individuals at the margin have higher expected returns than the individuals already attending college.

My results indicate that there is a notable fraction of poor individuals with high expected returns, who are at the margin of attending college, but who do not attend. This finding is suggestive of credit constraints for poor individuals, as these individuals lack resources and face high financing costs, or are completely prevented from borrowing, due to their lack of collateral. Thus credit constraints could be one of the driving forces of Mexico's large inequalities in access to higher education and low overall enrollment rates. Mexico's low government funding for student loans and fellowships for higher education, which is low even by Latin American standards, is consistent with this view. The results of my policy experiments suggest that the introduction of a means-tested student loan program could lead to large welfare gains by removing obstacles to human capital accumulation and fostering Mexico's development and growth.

It is important to note that the evidence above could be consistent with other factors also driving the poor's low college attendance rates. However, even if only some of the empirical patterns found in the data were driven by credit constraints, this would still imply scope for policy interventions. Furthermore, government policies such as student loan programs might still be recommendable if the steep income gradient mostly reflects heterogeneity in time preferences, for example. This could be the case if there are externalities from college attendance and social returns are correlated with private returns or if people have time-inconsistent preferences, e.g. they become more patient when getting older.

The rest of the paper is as follows. Section 2 gives background information on college attendance rates and costs and financing of college attendance in Mexico. Section 3 describes the survey data and the data on educational costs. Section 4 provides first evidence that the data is informative and illustrates that expected returns to college and perceived risk of future earnings are important determinants of college attendance decisions. Section 5 describes the model of college attendance choice and the use of the data on expected earnings, while section 6 estimates the cumulative distribution function of costs of college attendance and presents evidence that poor individuals face significantly higher costs. Section 7 derives and tests predictions of the model such as excess responsiveness of individuals, who face higher interest rates, to changes in direct costs. Section 8 shows how the LIV methodology can be used to derive "marginal" expected returns and to perform policy experiments, and evaluates potential welfare effects of a means-tested student loan program. Section 9 concludes.

2 Background Information on College Enrollment and on Costs and Financing of College Attendance in Mexico

In 2004 around 22% of adolescents of the relevant age group (18 to 24 years) were attending college in Mexico to receive an undergraduate degree ("licenciatura") (ANUIES, annual statistics 2004), which is significantly lower than in many other Latin American countries (see table 1). Mexico is characterized by large inequalities in access to college education for different income groups. In comparison to several other Latin American countries, such as Colombia, Argentina and Chile, only Brazil has a smaller fraction of poor students attending college (see table 1). Figure 1, which is based on the author's calculation using the Mexican Family Life Survey (MxFLS, 2003), displays college attendance rates of 18 to 24 year old high school graduates –thus already a selective group, as only about 54% of the relevant age group attain a high school degree– for different parental income quartiles measured in the last year before the college attendance decision. The attendance rate of individuals in the lowest parental income quartile is around 22% compared to 67% for the highest parental income quartile. The "Jovenes con Oportunidades" sample (2005) used in this paper consists of high school graduates from Oportunidades families and is thus only representative of about the poorest third of the high school graduate population (see section 3). The positive correlation between parental income and college attendance rate can also be found for this sample, but differences between poorest quartile (17%) and richest quartile (35%) are smaller, as every individual in the sample is relatively poor (see figure 2, Jovenes con Oportunidades 2005).

College attendance costs in Mexico pocket a large fraction of parental income for relatively poor families. Costs consist of enrollment and tuition fees, fees for (entrance) exams and other bureaucratic costs, health insurance (mandatory for some universities), costs for schooling materials such as books, costs for transport and/or room and board. I collected data on the two most important cost factors, tuition/enrollment costs and costs of living. Administrative data on tuition and enrollment fees per year from the National Association of Universities and Institutes of Higher Education (ANUIES) reveals a large degree of heterogeneity: Yearly tuition and enrollment costs vary between 50 pesos ("Universidad Autónoma de Guerrero", Guerrero) and 120,000 pesos ("Tecnológico de Monterrey", I.T.E.S.M. - Campus Puebla), which is equivalent to approximately 5 and 12,000 US$. The tuition cost measure that I use in my analysis is the minimum yearly tuition/enrollment fee of universities in the closest locality with at least one university (see section 3.3). Forty percent of the high school graduates face (minimum) tuition costs of over 750 pesos, which is equivalent to about 15% of median yearly per capita parental income. The other important cost factor depends on whether the adolescent has to move to a different city and pay room and board or whether a university is close to the location of residence, so that she can commute while taking advantage of the economies of scale of living with her family. I therefore construct a measure of distance to the closest university for each individual (see section 3.3).

In Mexico funding for higher-education fellowships and student loan programs is very limited and only about 5% of the undergraduate student population receive fellowships, while 2% receive student loans, which is low even compared to other Latin American countries (see table 1). The national scholarship program PRONABES was created in 2001 with the goal of more equal access to higher education at the undergraduate level. In 2005 funding of PRONABES amounted to 850 million pesos (equal to 40 US$ per student per year) and 5% of the undergraduate student population received a fellowship ("beca") in 2005 compared to 2% in 2001/02 (see Department of Public Education(SEP)), 2005). Eligibility for a fellowship is subject to a maximum level of family income (less than three times the minimum monthly salary, in special cases less than four times), a minimum GPA (8.0) and having been accepted at a public university or technical institute. After each year, the student has to prove that economic eligibility criteria are still met and that she is in good academic standing. In 2004/05 the fellowship consisted of a monthly stipend of 750 pesos –slightly more than half the minimum wage per month– in the first year of studies, and increased to 1000 pesos in the fourth year of studies. Student loan programs are also of minor importance in Mexico. Only about 2% of the national student population benefit from a student loan, which is low even compared to poorer Latin American countries, such as Colombia (9%) and Brazil (6%). In Mexico there are four different programs that offer student loans: the largest student loan program SOFES was implemented by a collaboration of private universities and is need-and-merit based, but students with collateral are preferred. This program offers loans to 1.5% of students. In addition there are three other very small state programs, ICEES in Sonora state, ICEET in Tamaulipas, and Educafin in Guanajuato.

3 Data Description

3.1 Survey Data

The survey "Jovenes con Oportunidades" was conducted in fall 2005 on a sample of about 23,000 15 to 25 year old adolescents in urban Mexico.[4] The sample was collected to evaluate the program

[4] Attanasio and Kaufmann (2007) use the same data set to perform diverse internal and external validity tests of the data on individuals' expectations of earnings, comparing moments of the individual earnings distributions for different groups –e.g. in terms of age and education of the respondent, ability and parental income–, and comparing cross-sections of expected earnings for different schooling degrees with cross-sections of earnings realizations using the Mexican Census (2000) and the MxFLS (2003). Lastly, they show that measures of subjective expectations are significant predictors of college and high school attendance choices, and provide some preliminary evidence that poor

"Jovenes con Oportunidades", which was introduced in 2002/03 and which gives cash incentives to individuals to attend high school ("Educacion Media Superior") and get a high school degree.

Thus primary sampling units are individuals, who are eligible for this program, that is students who are in their last year of junior high school (9th grade) or are attending high school (10 to 12th grade), who are younger than 22 years of age, and whose families are Oportunidades beneficiaries in urban Mexico.[5] As this paper analyzes the college attendance decision, I restrict the sample to 18/19 year old high school graduates, who either start to work (or look for work) or decide to attend college. The sample size is thus reduced to 3680 individuals.

The survey consists of a family questionnaire and a questionnaire for each 15 to 25 year old adolescent in the household. The data comprises detailed information on demographic characteristics of the young adults, their schooling levels and histories, their junior high school GPA, and detailed information on their parental background and the household they live in, such as parental education, earnings and income of each household member, assets of the household and transfers/remittances to and from the household. In addition the data contains information about individuals' subjective expectations of earnings as discussed next.

The survey contains a module that was designed to elicit information on the individual distribution of future earnings and the probability of working for different scenarios of highest completed schooling degree. After showing the respondent a scale from zero to one hundred to explain the concept of probabilities and going over a simple example, the following four questions on earnings expectations and employment probabilities were asked:

1. Each high school graduate was asked about the probability of working conditional on two different scenarios of highest schooling degree:
   Assume that you finish High School (College), and that this is your highest schooling degree. From zero to one hundred, how certain are you that you will be working at the age of 25?

2. The questions on subjective expectations of earnings are:
   Assume that you finish High School (College), and that this is your highest schooling degree. Assume that you have a job at age 25.

   (a) *What do you think is the maximum amount you can earn per month at that age?*

   (b) *What do you think is the minimum amount you can earn per month at that age?*

   (c) *From zero to one hundred, what is the probability that your earnings at that age will be at least x?*

individuals might be credit constrained. This paper investigates this latter issue in detail by testing predictions of a model of college attendance choice in the presence of credit constraints and performing policy experiments.

[5] The age of the individuals of the sample varies between 15 and 25, because the sample also includes the siblings of the primary sampling units.

x is the midpoint between maximum and minimum amount elicited from questions (a) and (b) and was calculated by the interviewer and read to the respondent.

3.2 Calculation of Expected Earnings, Perceived Earnings Risk, and Expected Gross Returns to College

In this section, I briefly describe how the answers to the three survey questions (2(a)-(c)) (see preceding section) are used to compute moments of the individual earnings distributions and expected gross returns to college (compare Guiso, Japelli and Pistaferri (2002) and Attanasio and Kaufmann (2007)). As a first step, I am interested in the individual distribution of future earnings $f(Y^S)$ for both scenarios of college attendance choice, where $S = 0$ ($S = 1$) denotes having a high school degree (college degree) as the highest degree. The survey provides information for each individual on the support of the distribution $[y^S_{min}, y^S_{max}]$ and on the probability mass to the right of the midpoint, $y^S_{mid} = (y^S_{min} + y^S_{max})/2$, of the support, $Pr\left(Y^S > (y^S_{min} + y^S_{max})/2\right) = p$. Thus I need to make a distributional assumption, $f(\cdot)$, in order to be able to calculate moments of these individual earnings distributions. In this paper, I assume a triangular distribution (see figure 3), which is more plausible than a stepwise uniform distribution as it puts less weight on extreme values. The first moment of the individual distribution is extremely robust with respect to the underlying distributional assumption (see Attanasio and Kaufmann (2007) for more details on the triangular distribution, alternative distributional assumptions and robustness checks).

Thus I can express expected earnings and variance of earnings for schooling degrees $S = 0, 1$ for *each* individual as follows:

$$\begin{aligned} E(Y^S) &= \int_{y^S_{min}}^{y^S_{max}} Y^S f(Y^S) dY^S \\ Var(Y^S) &= \int_{y^S_{min}}^{y^S_{max}} \left(Y^S - E(Y^S)\right)^2 f(Y^S) dY^S, \quad \text{for } S = 0, 1. \end{aligned}$$

I will perform the following analysis in terms of log earnings:

$$\begin{aligned} E(\ln(Y^S)) &= \int_{y^S_{min}}^{y^S_{max}} \ln(Y^S) f(Y^S) dY^S \\ Var(\ln(Y^S)) &= \int_{y^S_{min}}^{y^S_{max}} \left(\ln(Y^S) - E(\ln(Y^S))\right)^2 f(Y^S) dY^S \end{aligned}$$

and I can thus calculate expected (gross) returns to college as:[6]

$$\rho \equiv E(\text{return to college}) = E(\ln(Y^1)) - E(\ln(Y^0)).$$

There is a considerable amount of heterogeneity in expected gross returns to college: the fifth percentile of the expected return is $\rho_{0.05} = 0.18$ compared to the ninety-fifth percentile of $\rho_{0.95} =$

[6]This is just an approximation. In my theoretical model college choice is determined by a comparison of the expected present value of earnings in both college attendance states net of direct costs of college.

1.36. In addition, the following evidence suggests that expected returns are an important factor in individuals' college choice and that self-selection based on expected returns is important to take into account: the median expected gross return for high school graduates deciding to attend college is 0.66 compared to 0.60 for those, who decide to stop school after high school. A value of expected gross returns of 0.66 implies that expected college earnings are approximately 93% larger than expected high school earnings for individuals, who attend college.

To convince the reader of the validity of these measures of subjective expectations before using them in any further analysis, I show in section 4 that the expected return, the probability of working and the perceived risk of earnings in the two college attendance states are important determinants of college attendance choices even after controlling for an extensive list of individual and family background characteristics.

3.3 Data on Educational Costs

The previous subsection describes the calculation of expected gross returns. In addition it is important to have information on the direct costs of college attendance that people face to analyze their choices. Therefore I collected data on tuition costs and distance to college, which I will discuss in this section. In addition I will discuss the creation of measures capturing the financial situation of the high school graduate's family (survey data).

I use administrative data on tuition and enrollment fees per year from the National Association of Universities and Institutes of Higher Education (ANUIES).[7] In the following analysis I am using the following measure of tuition (and enrollment) costs: I determine the locality with universities that is closest to the adolescent's locality of residence (as described in the following paragraph), and then use the lowest tuition fee of all the universities/technical institutes that offer a four-year bachelor program in the relevant locality. Forty percent of adolescents face (minimum) tuition costs above 750 pesos, which is equivalent to 15% of median per capita parental income —while only representing a fraction of total college attendance costs—, and thus college attendance would imply a substantial financial burden for poor families.

Another important determinant of college attendance costs is the accessibility of universities (compare, e.g., Card (1995) and Cameron and Taber (2004)): costs can differ substantially depending on how far the adolescent lives away from the closest university. If she lives far away and thus has to move to a different city and pay room and board, this will be an important additional cost factor. Therefore, I collected information on the location of higher education institutions offering undergraduate degrees from the web page of the Department of Public Education (SEP). I determined the actual distance between the adolescent's locality of residence and the closest locality with

[7] The information I use to create a dataset of tuition costs is from ANUIES Catalogue of undergraduate degrees at universities and technical institutes 2004 ("Catalogo de Carreras de Licenciatura en Universidades e Institutos Tecnologicos 2004", see http://www.anuies.mx/).

higher education institutions using geo-code data on all relevant localities from the National Institute of Statistics, Geography and Information (INEGI) of Mexico.[8] About half of the adolescents live within a distance of 20 kilometers to the closest university, a distance that seems possible to commute daily with public transportation. Twenty-five percent of the adolescents live at a distance of between 20 and 40 kilometers, while the other quarter lives more than 40 kilometers away from the closest locality with universities.

Financing costs depend mainly on parental income and wealth, which determine the availability of resources –with opportunity costs of foregone savings– and the ability to collateralize and receive loans. The survey provides detailed information on income of each household member, savings if existent (only a very selective and richer group of households saves or borrows –4% of households have savings, while 5% borrow), durables and remittances. I create the following two measures: per capita parental income and an index of parental income and wealth. Per capita parental income includes parents' labor earnings, other income sources such as rent, profits from a business, pension income etc. and remittances, divided by family size. Median yearly per capita income is 5370 pesos (approximately 537 US$). The index of parental income and wealth is created by a principle component analysis of per capita income, value of durable goods and savings.

As I do not expect a linear effect of income and wealth on the ability to borrow, I add the measures in the form of dummies and use absolute thresholds for the parental income measure, as for the question of credit constraints absolute poverty in interaction with direct costs of schooling matters. For the indicator of parental income and wealth without natural unit, I use quartiles. I use the following per capita parental income thresholds: less than 5,000 pesos yearly (equivalent to 44% of the sample), between 5,000 and 10,000 pesos (34%), and more than 10,000 pesos (22%) of yearly per capita income. The reason for using these income thresholds is their approximate correspondence with eligibility requirements for receiving a fellowship. Therefore I can analyze whether eligibility for fellowships has an effect on college attendance. Nevertheless one should keep in mind that fellowships are quantitatively not very important: only 5% of the undergraduate student population received a fellowship in 2004 (see section 2). I use per capita income thresholds that are approximately equivalent to less than two times the minimum wage (less than 5,000 pesos per capita income yearly) –which are supposed to be the primary beneficiaries of the PRONABES fellowship–, and to between two and four times the minimum wage (between 5,000 and 10,000 pesos per capita income), while individuals with income of more than four times the minimum wage are not eligible.

[8] I use information on the location of public and private universities and technical institutes offering undergraduate degrees from the Department of Public Education (SEP, Secretaria de Educacion Publica - Subsecretaria Educacion Superior), http://ses4.sep.gob.mx/. I extracted geo-code information of all adolescents' localities of residence (around 1300) and of all localities with at least one university –in the states of our sample and in all neighboring states– from a web page provided by INEGI (Instituto Nacional de Estadistica, Geografia e Informatica), http://www.inegi.gob.mx/geo/default.aspx. My special thanks to Shaun McRae who helped extracting this data.

3.4 Two Survey Data Issues

3.4.1 Timing of the Survey

One important remark about the timing of the survey and the college attendance decision: One might be surprised about the fact that the following analysis –which requires knowledge of earnings expectations as well as of the actual college attendance decision– is possible with just one single cross-section. The Jovenes survey was conducted in October/November 2005 and thus two or three months after college had started.

To use this survey for the following analysis I have to make the assumption that individuals' information sets have not changed during this short period or have changed, but left expectations unchanged. The following two arguments support the assumption that during this period there has been no arrival of new information that changed earnings expectations: first, individuals learn about their ability relative to their peers before their attendance decision in July/August, because of entrance tests to college in February/March or in June/July, which individuals have to take to be admitted. Results of these tests are made public before the actual college attendance decision.[9] It is unlikely that individuals will learn significantly more about their ability in the first two or three months at university in addition to what they learned from their relative results at entrance exams. Second, additional learning about future college earnings has been shown to happen in the last year(s) of college (see Betts (1996) for evidence on the US) and not in the first few months. This is supported by evidence from my data: there is no significant difference in the cross-sections of expected returns to college for students, who just started college, compared to the one of students who are in their second year. On the other hand, return distributions are significantly different for students in higher years.

An additional potential concern is the behavioral response that individuals try to rationalize their choice two or three months later, i.e. individuals, who decided to attend college, rationalize their choice by stating higher expected college earnings (and/or lower expected high school earnings), and those, who decided not to attend, state lower expected college and higher high school earnings. To address this concern, I use the cross-section of earnings expectations of a cohort that is one year younger (just starting grade 12) as a counterfactual distribution for the cross-sectional distribution of expected earnings of my high school graduate sample before they had to decide about college attendance. I find no significant difference between the distributions of expected earnings of the two cohorts (Kolmogoroff-Smirnov test on equality of the distributions. See also figures 11 and 12 in Appendix C).

[9] Individuals can and usually do take entrance tests at several universities and if they are not admitted, they can continue to take tests at other universities.

3.4.2 Potential Sample Selection Problem

The interviewer visited the primary sampling units and their families in October and November 2005 and interviewed the household head or spouse using the family questionnaire and the high school graduate using the "Jovenes" questionnaire. In cases, in which the adolescent was not present, the household head or spouse also answered the "Jovenes" questionnaire. This mistakenly included the subjective expectations module, which was supposed to be answered by the adolescent directly. Therefore, the question on expected earnings was not answered by the adolescent herself for about half the sample of high school graduates. Table 2 compares summary statistics of important variables for the two groups of respondents. College attendance rates are significantly lower in the case that the adolescent responds, which raises concerns about sample selection in the case of using only adolescent respondents. Individuals who attend college –in particular if they live far from the closest university– are less likely to be at home at the time of the interview. Sample selection can –at least partially– be explained by observable variables: adolescent respondents live significantly closer to the closest university, are significantly more likely to be female (as many families do not want their female children to live on their own away from home) and have lower per capita household expenditures. On the other hand, variables such as expected returns to college as well as ability, father's years of schooling and per capita parental income do not differ significantly between the two groups.

I address the concern of potential sample selection in two ways: First, I use the full sample of both respondents, which is reasonable assuming that information sets and expectations of parents and their children are correlated (compare Attanasio and Kaufmann (2007), who show that the expectations of siblings are highly correlated and that –as a within-family comparison– siblings with higher than average GPA also have higher than average expected earnings and returns to college). Second, I use only the adolescent respondents and correct for sample selection by estimating jointly a latent index model for college attendance and a sample selection equation. As an exclusion restriction I use information on the date and time of the interview, which are strongly significant determinants of whether the respondent is the adolescent (see next section). Both approaches lead to very similar results, while sample selection on unobservables does not seem an important problem (the correlation between the error terms of the two equations is not significantly different from zero.) While I remain agnostic about who is the decision-maker, results are consistent with joint decision-making of parents and their child –the high school graduate– and with correlated information sets, as both approaches described above lead to very similar results.

4 College Attendance Decisions, Expected Returns to College and First Evidence on Credit Constraints

The goal of this section is twofold: before introducing a simple model of college attendance choice in the next section, I first provide evidence that the data on subjective expectations is informative. I show that individuals' expected returns to college, probabilities of work and perceived earnings risks in both college attendance states are important factors in their college attendance decisions. As a second step, I show that even after controlling for these important determinants –in addition to measures used in the existing literature on credit constraints such as parental background and ability–, parental income at the time of the college attendance decision remains a significant predictor of the college attendance choice.

To analyze the determinants of college attendance choices, I estimate the following latent index model, in which an individual chooses college if

$$S = 1 \Leftrightarrow S^* = \alpha_1 + \beta_1 \text{Exp Return} + \gamma_{1S} \text{Prob of Work}_S + \gamma_{1S} \text{Var of Log Earn}_S + \kappa_1 X + U_1 \geq 0, \quad (1)$$

and the choice depends on the expected return, the probability of work and the perceived risk of earnings in both college attendance states, S, and controls, X, such as a variety of individual and parental background characteristics as described later.

I address the potential sample selection problem (see previous section) in two ways: first I estimate equation (1) for the full sample, and second, I use only the adolescent sample and correct for sample selection by adding a sample selection equation, determining whether the respondent is the adolescent, $R = 1$ (assuming that S is observed only when $R = 1$):

$$R = 1 \Leftrightarrow R^* = \alpha_2 + \kappa_2 X + \lambda_2 Z + U_2 \geq 0, \quad (2)$$

and estimate both equations jointly, assuming that the latent errors, (U_1, U_2), are bivariate normal and independent of the explanatory variables with a zero-mean normal distribution and unit variances. As an exclusion restriction I use the time and date of the interview, Z, that is week of the year, day, time of the day and interactions between day and time of the day when the interview was conducted, which are strongly significant predictors. As results are very similar in both cases, I will only present and discuss results of the full sample (for results using the adolescent sample, see Appendix C).

Expected returns, the probability of working and the perceived earnings risk are important determinants of the college attendance decision. Table 3 illustrates that expected (gross) returns to college have a highly significantly positive effect on the college attendance decision. The stated probabilities of working have the expected signs, that is a higher probability of having a job with a high school degree decreases the likelihood of attending college (not significant), while an increase in the probability of working with a college degree significantly increases the likelihood of attendance. A higher perceived risk of college earnings significantly decreases the probability of attending college. The effect of expected returns is highly significant and similar in magnitude across all specifications (see also tables 4 to 6 in section 7), while the effect of the probability of work and the perceived earnings risk is less robust. Therefore, the main focus of the following analysis will be on expected returns.

Controlling for ability and parental background –conventionally used to capture differences in returns– shows that expected returns, probabilities of work and perceived risks are correlated with these measures (see smaller coefficient on expected returns in model 2 compared to model 1 in table 3), but that subjective expectations continue to play a significant role in determining college attendance decisions. One advantage of being able to control for expected returns directly is due to the multi-dimensionality of skills that can hardly be captured even with good data on test scores, while the individual has idiosyncratic knowledge about these skills. More importantly, what matters for the individual's decision is her perception of her skills and her beliefs about how they affect future earnings conditional on her information set at the time of the college attendance decision, which provides a strong rationale for using "perceived" returns.

At the same time, measures of ability/school performance such as junior high school GPA and parental education are strong predictors of college attendance after controlling for earnings expectations, suggesting a very important role for preferences for education (see model 2 of table 3).[10] In addition these measure are likely to also capture the probability of completing college.

With subjective expectations, I can address the question whether parental income is significant, *only* because it picks up differences in earnings expectations and perceived risk between poor and rich individuals. I find that per capita parental income at the time of the college attendance decision is still an important and significant determinant after controlling for earnings expectations and proxies for preferences (see table 3).[11] Thus parental income does not only have an effect on college attendance through its' effect on expected returns to college or on perceived earnings risk. This is stronger suggestive evidence for a role of credit constraints than in conventional approaches, but could also be due to unobserved heterogeneity in preferences between rich and poor individuals.

The goals of the next sections are as follows: the first goal is to gain a better understanding of the causes for the differences in college enrollment rates between poor and rich individuals and to

[10] I use GPA terciles, because schools do not use a standardized junior high school exam, so that GPA scores of different schools are not perfectly comparable, while a ranking based on GPA terciles is likely to be more meaningful. Results are very similar using mother's education, but there are even fewer mothers with high education than fathers, in particular very few with college education.

[11] I only report results using dummies for per capita parental income (see data section 3.3), while results using quartiles of the index for parental income and wealth are very similar (see Appendix C). I could in principle also control for per capita expenditures as a measure of longer-run (permanent) family income. The expenditure measure has the very important drawback that it contains schooling expenditures including those for the high school graduates who chose to attend college. Unfortunately it is impossible to separately identify which part of the costs is attributable to the high school graduate instead of her siblings. Adding per capita expenditures to table 3 does not significantly change results, in particular per capita parental income and the subjective expectations measures remain significant predictors (results from the author upon request).

analyze whether credit constraints might play an important role. The second goal is to evaluate potential welfare implications of policies, such as the introduction of a student loan program, which aim at increasing college attendance of the poor. To derive testable predictions about heterogeneity in interest rates that households face and to perform counterfactual policy experiments, I first introduce a simple model of college attendance choice and show how I make use of the data on earnings expectations in this model.

5 Model of College Attendance Choice

I model the college attendance decision based on the following assumptions:

Assumption 1 *Credit constraints are modeled as unobserved heterogeneity in interest rates, r_i.*

One special case would be two different interests rates, one for the group of credit constrained individuals, r_{CC}, and one for the group of individuals that is not constrained, r_{NC}, with $r_{CC} > r_{NC}$. In the literature heterogeneity of credit access has often been modeled as a person-specific rate of interest (see, e.g., Becker (1967), Willis and Rosen (1979) and Card (1995)). This approach has the unattractive feature that a high lifetime r implies high returns to savings after labor market entry. The testable prediction that I derive from this model (see next section) –that is excess responsiveness of poor individuals with respect to changes in costs– is robust with respect to this assumption, as it can also be derived, for example, from Cameron and Taber's model (2004), who use a similar framework, but assume that constrained individuals face higher borrowing rates than unconstrained individuals during school, but face the same (lower) borrowing rate once individuals graduate.

Assumption 2 *The problem is infinite horizon.*

Assumption 3 *Log earnings are additively separable in education and years of post-schooling experience. Individuals enter the labor market with zero experience and experience is increasing deterministically, $X_{i(a+1)} = X_{ia} + 1$, until retirement. Returns to experience are the same in both schooling states and for each individual.*

The assumption of log earnings being additively separable in education and experience is commonly used in the literature (compare, e.g., Mincer (1974)). Assuming a deterministic relationship for experience is equivalent to using potential labor market experience as a proxy for actual experience in a Mincer earnings regression. I abstract from work during studying, and thus assume that individuals enter the labor market –either at age $a = 18$ or at age $a = 22$ depending on college attendance decision– with zero experience. In a similar framework, Carneiro, Heckman and Vytlacil (2005) also make the assumption about returns to experience being the same in both schooling states and for all individuals.

Assumption 4 *Individuals have a common discount factor.*

The literature on credit constraints in general faces the problem of how to distinguish heterogeneity in borrowing rates from heterogeneity in time preferences. For example, Cameron and Taber (2004) assume one common discount factor for every individual and normalize the interest rate of the unconstrained individuals to be equal to this discount factor. If high-return individuals do not attend college because of a high discount rate, a policy intervention would have to be justified by high social returns to college that are correlated with private returns or with time-inconsistent preferences, e.g. people becoming more patient when getting older.

Assumption 5 *Individuals are risk-neutral.*

Thus –in a framework with uncertainty– the college attendance choice problem simplifies to maximizing the expected present value of earnings net of direct costs including monetized psychological costs or benefits.[12][13]

I model the college attendance decision of the high school graduate at age 18 as follows: An individual decides to attend college, $S = 1$, if the expected present value of college earnings minus the expected present value of high school earnings is larger than the costs (direct costs, i.e. monetary cost of tuition, books, transportation, board and room if necessary, and monetized psychological costs or benefits) of attending university:

$$\begin{aligned} S_i^* &= EPV(Y_i^1) - EPV(Y_i^0) - C_i \\ &= \sum_{a=22}^{\infty} \frac{E(Y_{ia}^1)}{(1+r_i)^{a-18}} - \sum_{a=18}^{\infty} \frac{E(Y_{ia}^0)}{(1+r_i)^{a-18}} - C_i \geq 0 \end{aligned} \tag{3}$$

In the following I will discuss how I use data on subjective expectations of earnings in this model, and how conventional approaches would use earnings realizations instead, having to correct for potential self-selection into college.

Assume that the economic model generating the data for potential outcomes is of the form:

$$\begin{aligned} \ln Y_{ia}^j &= \alpha_j + \beta_j' X_i + \gamma(a - s^j - 6) + U_{ia}^j \\ &= \alpha_j + \beta_j' X_i + \gamma(a - s^j - 6) + \theta_j' f_i + \epsilon_{ia}^j \quad \text{for } j = 0, 1 \text{ and } a = 18, ..., A, \end{aligned} \tag{4}$$

[12] As shown in section 4, individuals choose schooling also based on perceived earnings risk. In my future research, I will incorporate this additional determinant in a structural model, making use of subjective expectations to derive measures of perceived idiosyncratic risk that do not confound unobserved heterogeneity and risk.

[13] In order to use a common framework for deriving testable predictions and performing policy experiments applying the Local Instrumental Variables (LIV) methodology, the participation equation of college attendance has to be in additively separable form and therefore I need to rely on a relatively simple model of college attendance choice that consists of maximizing the expected present value of earnings net of costs. Carneiro, Heckman and Vytlacil (2005) use an even simpler set-up to motivate their selection equation of school choice in their LIV approach, analyzing the schooling decision without allowing for uncertainty.

where $j = 0$ denotes high school degree (12 years of schooling, $s^0 = 12$), and $j = 1$ college degree (16 years of schooling, $s^1 = 16$). In terms of observable variables a labels age, A age at retirement and $(a - s^j - 6)$ represents potential labor market experience, while X denotes other observable time-invariant variables. I assume that log earnings profiles are parallel in experience across schooling levels. Thus the coefficient on experience is the same in both schooling states, $\gamma_1 = \gamma_0 = \gamma$ (compare Mincer (1974) and Carneiro, Heckman and Vytlacil (2005)).

U^j represents the unobservables in the potential outcome equation, which are composed of a part that is anticipated at the time of the college attendance decision, $\theta_j' f_i$, and an unanticipated part ϵ_{ia}^j, where $E(\epsilon_{ia}^j) = 0$ for $j = 0, 1$.[14] Thus in this model self-selection into schooling on unobservables arises from $\theta_j' f_i$, which captures the anticipated part of the idiosyncratic returns (see equation (6)), while the unanticipated ϵ_{ia}^j can obviously not be acted upon. $\theta_j' f_i$ is unobserved in the conventional approach using earnings realizations, while $\theta_j' f_i$ is implicitly 'observed' in the approach using information on subjective expectations of earnings (see below for more details).

Thus the two potential outcomes relevant for the college attendance decision are:

$$\begin{aligned} \ln Y_{ia}^0 &= \tilde{\alpha_0} + \beta_0' X_i + \gamma a + \theta_0' f_i + \epsilon_{ia}^0 \\ \ln Y_{ia}^1 &= \tilde{\alpha_1} + \beta_1' X_i + \gamma a + \theta_1' f_i + \epsilon_{ia}^1, \end{aligned} \tag{5}$$

with $\tilde{\alpha_j} = \big(\alpha_j - \gamma(s^j + 6)\big)$ for $j = 0, 1$. The individual return to college in this framework can be written as:

$$\begin{aligned} \widetilde{\rho}_i &= \ln Y_{ia}^1 - \ln Y_{ia}^0 \\ &= \widetilde{\alpha} + (\beta_1 - \beta_0)' X_i + (\theta_1 - \theta_0)' f_i + (\epsilon_{ia}^1 - \epsilon_{ia}^0), \end{aligned}$$

where $\widetilde{\alpha} = (\tilde{\alpha_1} - \tilde{\alpha_0})$. The individual return to college can never be observed, as only one of the two potential outcomes is observable.

From the individual's answers on her expectations of earnings for age 25 ($a = 25$), one can derive the following information on expected earnings:

$$\begin{aligned} E(\ln Y_{ia}^0) &= \tilde{\alpha_0} + \beta_0' X_i + \gamma a + \theta_0' f_i \\ E(\ln Y_{ia}^1) &= \tilde{\alpha_1} + \beta_1' X_i + \gamma a + \theta_1' f_i, \end{aligned} \tag{6}$$

[14] In the 'conventional' Generalized Roy model (see, e.g. Carneiro, Heckman and Vytlacil (2005)) there is self-selection on U_0 and U_1 (see equation (4)) and no distinction between anticipated and unanticipated idiosyncratic returns. Carneiro, Heckman and Vytlacil (2005) analyze *ex post* returns in a framework without uncertainty as is common in the literature. I analyze school choice under uncertainty and *ex ante* returns. Therefore I distinguish between a part of the idiosyncratic returns that is anticipated and (potentially) acted upon at the time of the schooling decision and a part that is not anticipated and can thus not be acted upon (compare Cunha, Heckman and Navarro (2005) whose goal is to understand, which part of idiosyncratic returns is anticipated). Subjective expectations incorporate this information directly, as they only include the part that is anticipated.

Skill prices, θ_0, θ_1, can be allowed to differ across individuals. Also I do not need to assume rational expectations. Nevertheless, I do need assumptions about the way returns to experience enter and I can not allow for heterogeneity in returns to experience, because the questions about earnings expectations have only been asked for one point of the life-cycle, that is for age 25.[15] Using the information given in (6), I can derive an expression for expected gross returns:

$$\begin{aligned} \rho_i &= E(\ln Y_{ia}^1 - \ln Y_{ia}^0) \\ &= \widetilde{\alpha} + (\beta_1 - \beta_0)' X_i + (\theta_1 - \theta_0)' f_i. \end{aligned} \tag{7}$$

To estimate the model of college attendance choice (see equation (3), I make use of the data on subjective earnings expectation (6) applying the following approximation $E(Y_{ia}) \equiv E(e^{\ln Y_{ia}}) \cong e^{E(\ln Y_{ia}) + 0.5 Var(\ln Y_{ia})}$. Given the assumptions about experience, I can rewrite the participation equation (3) in terms of expected gross returns to college (see Appendix B for the derivation):

$$\begin{aligned} S_i^* &= f\left(r_i, \rho_i, \sigma_i^0, \sigma_i^1, C_i, E(\ln Y_{i25}^0)\right) \\ S_i &= 1 \text{ if } S_i^* \geq 0 \\ S_i &= 0 \text{ otherwise,} \end{aligned} \tag{8}$$

where S_i is a binary variable indicating the treatment status.

In the next two sections, I first estimate cumulative distribution functions of costs of college attendance for different income categories and second, I derive and test the prediction of heterogeneity in the interest rates that households face.

6 The Cumulative Distribution Function of Costs of College Attendance

The participation equation of college attendance, as derived from the model in the previous section (see equation 8 and Appendix B), is additively separable in expected gross returns, ρ, and a cost term reflecting total college attendance costs, K, which depend on direct costs such as tuition costs, the interest rate that the household faces and psychological costs:[16]

$$S = 1 \Leftrightarrow S^* = \rho - K \geq 0$$

With data on each individual's expected return, ρ and on her decision to attend college or not, $S = 0, 1$, it is possible to derive the cumulative distribution function (c.d.f.) of overall costs of

[15] Belzil (2001) suggests that heterogeneity in returns to experience is important in addition to heterogeneity in returns to schooling. This has rarely been taken into account in the current literature. It would be an interesting second step to also take into account heterogeneity in returns to experience by asking about expected earnings for several points of the life-cycle.

[16] This is an approximation to the participation equation as derived from the model, as it neglects higher order terms of ρ, i.e. ρ^2, ρ^3 etc (see Appendix B).

college attendance, $F_K(k)$, assuming that overall costs, K, are independent of the expected returns, ρ:

$$Pr(S=1|\rho=\tilde{\rho}) = Pr(K \leq \tilde{\rho}|\rho=\tilde{\rho}) = F_{K|\rho=\tilde{\rho}}(\tilde{\rho}) = F_K(\tilde{\rho}). \tag{9}$$

Intuitively, the fraction of the people expecting return $\tilde{\rho}$, who decide to attend college, reflects the fraction of people with costs smaller than expected return $\tilde{\rho}$.

Being able to estimate the cumulative distribution function of costs can improve our understanding of the causes for the large differences in enrollment rates between poor and rich individuals. Finding that the cumulative distribution function of costs of the poor stochastically dominates the one of the rich individuals suggests that poor individuals face significantly higher costs of financing due to lack of collateral or potentially higher unobserved psychological costs (or both). Direct costs of college are likely to be similar for poor and rich individuals, or even smaller for the poor, if there are tuition waivers.

I estimate $Pr(S=1|\rho=\tilde{\rho})$ over the support of ρ by performing Fan's (1992) locally weighted linear regression of college attendance, S, on the expected return, which indirectly implies estimating the cumulative distribution function of overall costs, $F_K(k)$, given the independence assumption, $\rho \perp K$.[17] The c.d.f. of costs can only be estimated over the support of the expected return (see equation (9)).[18]

To compare the cumulative distribution function of costs for different income classes, I perform a locally weighted linear regression for "low" income individuals (yearly per capita income less than 5,000 pesos), "middle" income (between 5,000 and 10,000 pesos) and "high" income individuals (more than 10,000 pesos). Note though that even the "high" income individuals are not rich, as the sample only comprises about the poorest third of the high school graduate population. Figure 7 shows that the c.d.f. of costs for poorer individuals is shifted to the right. For every given level of costs on the support, e.g. $K = 0.6$, there is always a larger fraction of poor individuals facing higher costs (more than 75% of the poor face costs $K > 0.6$) than rich individuals (only 55% face costs $K > 0.6$). To put it differently, among individuals with expected returns around $\rho = 0.6$, 45% of rich individuals attend, but only 25% of the poor, that is poor individuals require higher expected returns to be induced to attend college.

To analyze whether there is a statistically significant difference in the cumulative distribution function of costs of the poorer versus the richer individuals, I calculate point-wise confidence intervals applying a bootstrap procedure. Figure 8 plots the c.d.f. of poor and rich individuals with

[17] I use a Gaussian kernel and a bandwidth of 0.3, as the sample sizes for the different income groups (high, middle, low) are relatively small with 605, 923 and 1171 observations respectively. The choice of the kernel does not affect the results, while a smaller bandwidth will lead to a more wiggly line, while not changing the result that there is a significant right shift in the c.d.f. of costs for poorer individuals (see below).

[18] Note that I drop large outliers of expected returns in the plotted graphs (upper 8%), thus being left with a support of [0.05, 1.2]. Including them would cause the nonparametric regression line to start sloping down for returns larger than 1.1, which seems to be driven by some outliers where people state very high returns but do not attend.

95%-confidence intervals and illustrates that the c.d.f. of costs of the poor is significantly shifted to the right compared to the one the "rich" for a wide range of the support, $K \in [0.25, 1.1]$. This is also true comparing the middle and the rich income group for $K > 0.35$ (see figure 9). Comparing the middle and low income group, confidence intervals slightly overlap, but plotting and bootstrapping the distance $g(x) = \hat{F}_{K,Mid}(x) - \hat{F}_{K,Low}(x)$ point-wise for each x on the support, one can reject the null of $g(x) \leq 0$ for part of the support on 10% or 5% (see figure 10).

Thus, the cumulative distribution function of costs of poorer individuals is significantly shifted to the right compared to the one of richer individuals, that is poorer individuals face significantly higher costs of college attendance and thus require higher expected returns to be induced to attend college. To understand the role of the different cost components and whether credit constraints might play an important role in the low enrollment rate of poor Mexicans, I derive a testable prediction of heterogeneity in interest rate from the model of college attendance choice (see section 5) in the next section.

7 Excess Responsiveness to Changes in Direct Costs

The college attendance choice model described in section 5 implies that individuals who face a high interest rate, r, react more strongly to changes in direct costs (see equation (24) in Appendix B):

$$\left| \frac{\partial S^*}{\partial C} \right| \quad \text{is increasing in} \quad r. \tag{10}$$

Intuitively, a one-unit increase in costs has to be financed through a loan with interest rate r (or foregone savings), and thus has larger negative effects on individuals facing high financing costs.

I test this prediction using dummies for groups, who are likely to face different interest rates if credit constraints are important, such as different categories of parental income (and wealth). Thus I test for excess responsiveness of poor individuals with respect to changes in direct costs, such as tuition costs and distance to college.

The prediction of excess responsiveness of potentially credit constrained groups to changes in direct costs is not specific to my model, but can be derived from a more general class of school choice models, for example from the model of Cameron and Taber (2004), which is based on different assumptions concerning heterogeneity in interest rate (see section 5). Card (1995), Kling (2001) and Cameron and Taber (2004) use a similar test interacting variables such as parental income and race with a dummy for the presence of a college in the residential county.[19]

Compared to conventional approaches having information on subjective expectations has the following two advantages: First, I can control directly for one important set of determinants of college attendance, that is expected returns and perceived risk of earnings, and thereby avoid a

[19] Card and Kling find evidence of important credit constraints for an older cohort of the National Longitudinal Survey (NLS Young Men), while Cameron and Taber do not find evidence of credit constraints for the U.S.A. using the NLSY 1979.

potential omitted-variable problem.[20] This makes my test more robust and enables me to analyze the validity of the test used without controlling for these determinants. Second, being poor does not necessarily imply being credit constrained: only poor individuals with high expected returns are potentially prevented from attending college due to high financing costs, while poor low-return individuals would not decide to attend college anyways. Thus with information on expected returns I can refine the test and test for excess responsiveness of poor *high-expected-return* individuals to changes in direct costs.

In the following, I present results for the full sample using per capita parental income dummies as proxies. Results for the adolescent sample correcting for potential sample selection and results using dummies of the indicator for parental income and wealth are very similar (see Appendix C).

The first measure of costs that I use is the distance of the adolescent's locality of residence to the closest university (see data section 3.3). As shown in section 4 living further away from the closest university has significantly negative effects on the probability to attend college. Table 4 illustrates that the negative effect of a larger distance to college is only significant for the poorest individuals: living 20 to 40 kilometers away from college instead of a distance of less than 20 kilometers decreases the probability of attending by about 6 percentage points for the poorest income category (living more than 40 kilometers away has a negative effect on all income categories, but is never significant). In this case being able to control for earnings expectations does not change the results, despite the fact that higher expected return and a higher probability of work with a college degree have large positive effects on attendance.

I use yearly tuition and enrollment fees as the second cost measure, that is a dummy for tuition costs above 750 pesos, which is equivalent to about 15% of median yearly per capita income and thus represents a significant financial burden for poor individuals. Table 5 shows that higher tuition costs have a significantly negative effect on the poorest individuals decreasing their likelihood of attendance by 7.5 percentage points. The effect on individuals in the "middle" income category is still negative, but smaller in magnitude and not significant, while the effect on richer individuals is in fact positive. This could be driven by the fact that for rich individuals living close to an expensive "high quality" university increases the likelihood to attend. This is particularly likely for female adolescents, who –according to family traditions– should not move to a different city on their own, unless married or with someone of the family.

The results show that there is excess responsiveness of poor individuals with respect to a change

[20] Omitting expected returns in the participation equation could cause a problem as in this case the error term would contain unobserved heterogeneity in ability reflecting unobserved differences in expected returns (see equation (7) and (8) in the previous section), which might be correlated with the interaction term of parental income and direct college costs. It has been shown that measures of schooling costs, such as distance to college, are correlated with observed ability measures such as AFQT score, and are thus most likely also correlated with unobserved ability (see Carneiro and Heckman (2002)). Similarly the interaction between parental income and direct college costs could be correlated with unobserved ability, which might hamper the interpretation of results of the test. Making use of data on expected returns and perceived risks directly can avoid this specific endogeneity concern.

in direct costs (differential effect significant on 1% for tuition costs, not significant on conventional levels for distance after controlling for tuition). If this effect is a result of credit constraints, it should be driven by poor individuals with high expected returns. Table 6 shows that in fact poor high-expected-return individuals are the ones, who are most responsive to changes in direct costs in comparison to all other groups.

While controlling for measure of expected returns and higher moments does not change the results significantly, taking into account that what matters is being poor *and* having high expected returns makes a difference: for the adolescent sample, tuition appears not to have any significant effect when purely being interacted with income dummies, while it does in fact have a significantly negative effect for poor individuals with high expected returns. The above results are consistent with the predictions of a model with credit constraints, and thus provide suggestive evidence of their impact on college attendance decisions of poor Mexicans with high expected returns. Nevertheless, this result could still be –at least partially– driven by unobserved heterogeneity in preferences.

8 Policy Experiments

The results above indicate that poor individuals face significantly higher costs and that poor high-expected-return individuals are most sensitive to changes in direct costs. These findings are consistent with credit constraints, which would create scope for policy interventions such as student loan programs. In this section, I evaluate potential welfare implications of the introduction of a means-tested student loan program, by analyzing the effects of a change in the interest rate faced by poor (or poor and able) individuals. I estimate the change in college attendance rates, and derive the expected returns for the individuals who change their college attendance decision in response to the policy ("marginal" expected returns).

As discussed above, the evidence presented is suggestive of credit constraints, but leaves the possibility of other factors also driving the low college attendance rates among poor. It is worth noting that even if some but not all of the empirical patterns found is driven by credit constraints, this would imply scope for policy interventions. Furthermore, government policies such as student loan programs might still be recommendable, even if the empirical fact mostly reflects heterogeneity in time preferences, for example. This could be the case, if there are externalities from college attendance (correlated with private returns), or if people have time-inconsistent preferences, e.g. they become more patient when getting older.

I perform policy experiments and derive marginal returns using the college attendance choice model of section 5 and applying the Local Instrumental Variables methodology of Heckman and Vytlacil (2005) to a setting with subjective expectations of earnings instead of earnings realizations.

The comparison between "marginal" expected returns of individuals, who switch participation in response to a policy, and average expected returns of individuals attending college is interesting not only from a policy-evaluation point of view. If "marginal" expected returns are higher than expected returns of individuals, who attend college, then individuals at the margin have to face particularly high unobserved costs, as otherwise they would also be attending college given their high expected returns.

This idea follows Card's interpretation (Card (1999, 2001)) of the finding that in many studies devoted to estimating the "causal" effect of schooling, instrumental variable (IV) estimates of the return to schooling exceed ordinary least squares (OLS) estimates. Since IV can be interpreted as estimating the return for individuals induced to change their schooling status by the selected instrument, finding higher returns for "switchers" suggests that these individuals face higher marginal costs of schooling. In other words, Card's interpretation (2001) of this finding is that "marginal returns to education among the low-education subgroups typically affected by supply-side innovations tend to be relatively high, reflecting their high marginal costs of schooling, rather than low ability that limits their return to education."

This argument has the following two problems (compare Carneiro and Heckman (2002)): first, the validity of the instruments used in this literature is questionable,[21] and second, even granting the validity of the instruments, the IV-OLS evidence is consistent with models of self selection or comparative advantage in the labor market even in the absence of credit constraints. The problem is that ordinary least squares does not necessarily estimate the average return of those individuals attending college, $E(\beta|S=1) \equiv E(\ln Y_1 - \ln Y_0|S=1)$, which would be the correct comparison group to test for credit constraints. Rather OLS identifies $E(\ln Y_1|S=1) - E(\ln Y_0|S=0)$, which could be larger or smaller than $E(\beta|S=1)$.[22]

Subjective expectations of earnings enable me to directly get at the expected returns of individuals attending college, while I estimate the missing part of this test –the "marginal" expected return of those individuals who respond to a change, for example, in distance to college–, using the Local Instrumental Variable (LIV) approach of Heckman and Vytlacil (2005). In contrast to the conventional approach, I do not face the problem of missing counterfactual earnings, but have data on expected earnings for both schooling scenarios and can thus compute expected gross returns for each individual. Therefore, I do not have to rely on the unverifiable assumption that direct costs to college, such as distance to college, satisfy the exclusion restriction, but I can test this assumption.

Figures 13 and 14 (see Appendix C) show a scatter plot of expected returns and distance to college and a locally weighted linear regression line of expected returns on distance to college, from which no pattern is apparent. In table 17 (see Appendix C) I regress expected returns on observable characteristics of the individual and her family background, such as GPA of junior high

[21] Carneiro and Heckman (2002) show for several commonly used instruments using the NLSY that they are either correlated with observed ability measures, such as AFQT, or uncorrelated with schooling.

[22] $E(\ln Y_1|S=1) - E(\ln Y_0|S=0) = E(\beta|S=1) + (E(\ln Y_0|S=1) - E(\ln Y_0|S=0))$, where the last bracket could be larger or smaller than zero. In particular, in the case of comparative advantage, the OLS estimate will be smaller than the average return of those attending. This could lead to a case in which IV estimates are larger than OLS estimates, but smaller than the average return of those attending, from which one would wrongly conclude that credit constraints are important.

school, father's education (same result using mother's education), per capita parental income, and on polynomials of distance to college. For the full sample I find that expected returns and distance to college are significantly positively correlated, though the coefficient on distance is small. For the adolescent sample –controlling for sample selection by applying a Heckman two-step procedure– the coefficients on the polynomials of distance to college are not significantly different from zero. Note that the table presents results for distance and squared distance, but adding further polynomials does not change this result, while for the full sample all polynomials become insignificant once higher than second-order polynomials are included. The result for the adolescent sample is comforting, as this implies that at least a necessary condition for the validity of the exclusion restriction is satisfied. Nevertheless, one would like to allow distance to college to enter in this regression in a completely flexible form, $h(C)$. This is in principle possible by estimating a partially linear regression model, but is complicated by a potential sample selection problem for the adolescent sample. Results of this procedure will be included in the next version of the paper. Thus the exclusion restriction is violated for the full sample, but I can not reject the hypothesis that it holds for the adolescent sample. Therefore, I perform the following analysis using the adolescent sample. One should keep in mind that previous results were similar using both approaches, that is using the full sample and using the adolescent sample correcting for sample selection, and that results suggested that sample selection on unobservables did not seem to be an issue.

8.1 Implications of Credit Constraints for Marginal Returns to College

From the latent index model (8), I can derive the return at which an individual is exactly indifferent between attending college or not, so that $S^* = 0$:

An individual is indifferent between attending college or not at the following -implicitly defined- "marginal" return, ρ^M,

$$S_i^* = f\left(r_i, \rho_i^M, \sigma_i^0, \sigma_i^1, C_i, E(\ln Y_{i25}^0)\right) = 0 \tag{11}$$

The presence of credit constraints has the following implication for marginal returns: implicit differentiation of equation (11) leads to:

$$\frac{d\rho_i^M}{dr_i} = -\frac{\partial f/\partial r_i}{\partial f/\partial \rho_i^M} > 0,$$

and thus credit constrained individuals, who face higher borrowing costs, $r_{CC} > r_{NC}$, have higher marginal returns (ceteris paribus) than those individuals on the margin who are not credit constrained:

$$\rho^M(r_{CC}) > \rho^M(r_{NC}).$$

In the next subsections I illustrate how the marginal return to college can be derived, and how it can be used to perform policy experiments.

8.2 Derivation of the Marginal Return to College

This section follows Carneiro, Heckman and Vytlacil (2005) and Heckman and Vytlacil (2005) in their derivation of the "Marginal Treatment Effect" (MTE). Nevertheless, their goal is to get estimates of summary measures of the return-to-schooling distribution purged from selection bias and the MTE is just a tool in this encounter. In contrast to the conventional approach, I do not have to deal with self-selection problems because with subjective expectations of earnings, I "observe" each individual in both schooling states, while I am interested in the marginal return to college for its own sake.

One important first step in the derivation and estimation of the marginal return to college is the estimation of the propensity score $P(Z) \equiv P(S=1|Z=z)$, which represents the probability of attending college conditional on observables Z, making use of the participation equation as derived from the school choice model in section 5. Note that I perform the following monotonic transformation of the participation equation, $S^* = \nu(Z) - V$:

$$S^* \geq 0 \Leftrightarrow \nu(Z) \geq V \Leftrightarrow F_V(\nu(Z)) \geq F_V(V),$$

and define $\mu(Z) \equiv F_V(\nu(Z))$ and $U_S \equiv F_V(V)$. In this case $U_S = F_V(V)$ is distributed uniformly, $U_S \sim$ Unif$[0,1]$.[23] Therefore, the participation equation can be written as follows:

$$S^* \geq 0 \Leftrightarrow P(Z) = \mu(Z) \geq U_S.$$

An individual indifferent between attending college or not is characterized by $U_S = \mu(Z) = P(Z)$. It is thus possible to estimate U_S for the indifferent individual by estimating the propensity score $P(Z)$, i.e. the probability of attending college.

This will allow me to derive the marginal return to college or Marginal Treatment Effect (MTE), which in this framework will be defined as:

$$\Delta^{MTE}(u_S) = E(\ln Y_1 - \ln Y_0 | U_S = u_S) = E(\rho | U_S = u_S) \tag{12}$$

and it represents the average gross gain to college for individuals who are indifferent between attending university or not at the level of unobservables $U_S = u_S$.

One important drawback of the LIV methodology is that the analysis relies critically on the assumption that the selection equation has a representation in additively separable form, $S^* = \mu(Z) + U_S$ (see, e.g., Heckman and Vytlacil (2005) and Heckman, Urzua and Vytlacil (2006)). Using information on subjective expectations of earnings, I can write the participation equation (8) as derived from the school choice model as the following fourth-order polynomial in the unobservable interest rate, $1+r$ (see Appendix B for the derivation):

$$S_i^* \geq 0 \Leftrightarrow (1+r_i)^4 - A(Z_i;\theta)(1+r_i)^3 - B(Z_i;\theta) \leq 0, \tag{13}$$

[23] U_S is distributed uniformly, as $Pr(U_S \leq \mu(Z)) = Pr(V \leq F_V^{-1}(\mu(Z))) = F_V(F_V^{-1}(\mu(Z))) = \mu(Z)$. Thus the propensity score is equal to $P(Z) \equiv Pr(S=1|Z=z) = Pr(S^* \geq 0|Z) = Pr(U_S \leq \mu(Z)) = \mu(Z)$.

where $A(Z_i;\theta), B(Z_i;\theta) > 0$ are functions of the observables $Z_i = \left(\rho_i, \sigma_i^0, \sigma_i^1, C_i, E(\ln Y^0)\right)$ including the expected return ρ_i from the data on subjective expectations and a coefficient vector, θ. One can show that this fourth-order polynomial equation has exactly one positive root with $1 + r_i \geq 0$, which can be analytically computed, so that the following holds:

$$g\left(Z_i;\theta\right) \geq 1 + r_i \Rightarrow (1+r_i)^4 - A(Z_i;\theta)(1+r_i)^3 - B(Z_i;\theta) \leq 0.$$

Defining V_i as deviations from the mean interest rate, $r_i = \bar{r} + V_i$, the selection equation can be rewritten in the following additively separable form:

$$\begin{aligned} S_i^* &= -(1+\bar{r}) + g\left(Z_i;\theta\right) - V_i \\ S_i &= 1 \;\text{ if }\; S_i^* \geq 0 \\ S_i &= 0 \;\text{ otherwise.} \end{aligned} \tag{14}$$

I assume $V_i \sim N(0,1)$ and estimate the propensity score $P(Z)$ using a Maximum Likelihood procedure.

With the help of the predicted values of the propensity score, $\widehat{P(z)}$, I can define the values $u_S = F_V(V)$ over which the marginal return to college (MTE) can be identified:[24] the MTE is defined for values of $\widehat{P(z)}$, for which one obtains positive frequencies for both subsamples $S = 0$ and $S = 1$. The observations for which $\widehat{P(z)}$ is outside of the support are dropped.[25]

As a second step in the derivation of the marginal return to college one can show that the following equality holds:

$$\Delta^{MTE}(u_S) \equiv E\left(lnY_{it}^1 - lnY_{it}^0 | U_S = p\right) = \left.\frac{\partial\left\{\int_0^p E\left(lnY_{it}^1 - lnY_{it}^0 | U_S = p\right) dU_S\right\}}{\partial p}\right|_{p=u_S}.$$

The integral can be rewritten as (see Appendix B):

$$\begin{aligned} \int_0^p E\left(lnY_{it}^1 - lnY_{it}^0 | U_S = p\right) dU_S &= pE\left(lnY_{it}^1 - lnY_{it}^0 | U_S \leq p\right) \\ &= pE\left(lnY_{it}^1 - lnY_{it}^0 | P(Z) = p, S = 1\right). \end{aligned} \tag{15}$$

With subjective expectations of earnings one has data on each individual's expectation of earnings in both schooling states, and thus also for those individuals who decide to attend college,

[24]Identification of the MTE depends critically on the support of the propensity score (see Heckman and Vytlacil (2001)). As conventional treatment parameters such as ATE and TTE are weighted averages of the MTE (see, e.g., Heckman and Vytlacil (2005)), also the derivation of those parameters depends on the support. Support problems can lead to substantial biases. With subjective expectations I have direct information on the TTE, while the derivation of the policy relevant treatment effect is not affected by support problems, as –in this derivation– the MTE only has positive weight over its' support.

[25]Even after trimming, the sparseness of data in the tails results in a large amount of variability in the estimation of the MTE for values of p closer to the corners of the support.

$E\left(lnY_{it}^1 - lnY_{it}^0|S=1\right)$. I estimate $P(Z)$ in a first step and therefore have a value $\widehat{P(z)} = p$ for each individual.

Finally I fit a nonparametric regression of

$$m(p) = pE[\ln Y_{it}^1 - \ln Y_{it}^0|P(Z) = p, S = 1]$$

on the propensity score using a locally weighted regression approach (Fan (1992)). The main strength of this approach is that it assumes no functional form and delivers a natural estimator of the slope of the regression function $m(p)$ at p which is equivalent to the MTE for the different points on the grid, $p = u_S$.

The implementation of the approach is as follows: I divide the range of my independent variable p into a grid of points and estimate a series of locally weighted regressions for each point on the grid, where the weights are larger the closer the observations are to the specific point on the grid. The choice of kernel and bandwidth define "close".[26] The predicted value of this regression at p is then the estimated value of the regression function at the grid point, i.e., $\hat{m}(p) = \hat{\beta}_0(p) + \hat{\beta}_1(p)p$. $\hat{\beta}_1(p)$ is a natural estimator of the slope of the regression function at p and thus estimates the MTE for different values of $p = u_S$, as $\partial m(p)/\partial p = \Delta^{MTE}(u_S)$. I calculate standard errors by applying a bootstrap over the whole procedure described in this section.

To perform policy experiments, I introduce the following notation: the "Policy Relevant Treatment Effect" ($PRTE$) is a weighted average of the marginal returns to college ($\Delta^{MTE}(u_S)$), where the weights depend on who changes participation in response to the policy of interest (compare Heckman and Vytlacil (2001)). One important assumption underlying this analysis is that the participation equation continues to hold under hypothetical interventions. The $PRTE$ can be written as:

$$PRTE = \int_0^1 MTE(u)\omega(u)du, \tag{16}$$

where the weights are determined by:

$$\omega(u) = \frac{F_P(u) - F_{P^*}(u)}{E(P^*) - E(P)}. \tag{17}$$

P is the baseline probability of $S = 1$ with cumulative distribution function F_P, while P^* is defined as the probability produced under an alternative policy regime with cumulative distribution function F_{P^*}. The intuition is as follows: given a certain level of unobservables, u, those individuals with $P(Z) > u$ will attend college, which is equivalent to a fraction $1 - F_P(u)$. A reduction, for example, in direct costs, Z, will lead to a new larger $P(Z^*)$. Thus for a given u, there are now more people deciding to attend college, $1 - F_{P^*}(u)$, and the change can be expressed as $F_P(u) - F_{P^*}(u)$. The weight is normalized by the change in the proportion of people induced into the program, $E(P^*) - E(P)$, to express the impact of the policy on a per-person basis.

[26] The choice of the kernel is not a critical one (see, e.g., Deaton (1997)) and my results are robust with respect to this choice. On the other hand, the choice of the bandwidth is much more crucial as it controls the trade-off between bias and variance. I present results for several different bandwidths.

The following is a special case of a $PRTE$: Consider a policy that shifts Z_k (the kth element of Z) to $Z_k + \varepsilon$. For example, Z_k might be the tuition faced by an individual and the policy change might be to provide an incremental tuition subsidy of ε dollars. Suppose that $S^* = Z'\gamma + V$, and that γ_k (the kth element of γ) is nonzero. The resulting $PRTE$ is:

$$PRTE_\varepsilon = E(\rho_i | Z'\gamma \leq V \leq Z'\gamma + \varepsilon\gamma_k), \tag{18}$$

i.e., $PRTE_\varepsilon$ is the average return among individuals who are induced into university by the incremental subsidy.

I will use the $PRTE$ to evaluate different policies by deriving the average marginal expected return of individuals induced to change their schooling status as a response to these policies, and compare the results to the average return of those attending.

8.3 Estimation of the Marginal Return to College

This section describes how the estimation of the marginal return to college is implemented, and discusses the empirical results of this estimation, while the next section discusses the results of the policy experiments. I estimate the propensity score, i.e. the probability of attending college, from selection equation (14) –as derived from the simple college attendance choice model (see section 5)– using a Maximum Likelihood procedure. In order to empirically implement the notion of costs, C, from my theoretical model, I use the following auxiliary regression containing distance to the closest university, "Univ Dist", distance squared, "Univ Dist Sq", and state fixed effects to capture differences in direct costs, and mother's education and GPA of junior high school to capture preferences for education of the individual and her family and thus monetized psychological costs/benefits of attending college:[27]

$$C = \delta_0 + \delta_1 \text{Univ Dist} + \delta_2 \text{Univ Dist Sq} + \delta_3 \text{GPA} + \delta_4 \text{Mother's schooling} + \delta_5 \text{State dummies}.$$

The results of the Maximum Likelihood Estimation of the propensity score are displayed in table 7. The variables capturing costs of attending college, i.e. distance to the closest university, distance squared, GPA of junior high school and mother's schooling attainment are all highly significant and with the expected sign, as are expected returns to college and a term capturing the difference in variances of college and high school earnings.

In order to give an idea of the magnitude of the effects, I present tables 8 and 9. In table 8 I illustrate the effect of a change in the distance to the closest university, of having a mother with one more year of schooling and of having a one percentage point higher GPA. The baseline case evaluates all explanatory variables at their medians, that is living about 18km away from the

[27] I use mother's schooling as the father is not present in some of the households and would thus lead to more missing values. The results are robust with respect to using father's schooling instead. In contrast to previous specifications, I add mother's years of schooling and km-distance directly instead of using dummies, as it is hard to achieve convergence otherwise.

closest university, having a mother who has five years of completed schooling and having a GPA of 82%, which leads to a predicted probability of attending college of 22%. Living 5km closer to the closest university increases the probability of attending by 1.3 percentage points that is by about 6%.[28] Having a mother with one year more of schooling increases the probability of attending by 1.8 percentage points, while having a one percentage point higher GPA increases the probability of attending by 0.7 percentage points. Table 9 displays the effect of an increase in expected returns to college for different baseline cases. The effect of a 10 percentage point (or 16%) increase in expected returns increases the probability of attending college by about 1 percentage point (or 5%). Note that the effect of an increase in return doubles if the individual faces lower direct costs (lives 5km closer to the closest university), which is consistent with the presence of credit constraints as individuals, who face lower costs are less likely to be credit constrained, and can thus act upon higher expected returns more easily.

Figure 4 depicts the density of the predicted probability of attending college for high school graduates, who decided to attend college, and those, who stopped school after high school, using smoothed sample histograms. It illustrates that the probability of attending college of the "Jovenes" sample is generally relatively low, but that there is a right-shift in the density for high school graduates, who decided to attend college, with a mean (median) probability of about 36% (34%), while the mean (median) probability of attending for those who stopped is around 29% (27%). Figure 4 illustrates that there is little mass outside of the interval 0.1 and 0.8, so that the support over which I estimate the marginal return to college is for p in the interval $[0.1, 0.8]$.

As the last step I perform Fan's locally weighted regression to estimate the marginal return to college by estimating a series of locally weighted regressions on each point on the grid of $u_S = P(Z)$ using a step size of 0.01 over the support of $P(Z)$. The estimators of the slope of these regressions for the different points on the grid are the marginal returns for different levels of unobservables $u_s = P(Z)$ (as illustrated in the previous section). Figure 5 displays the marginal return to college for three different bandwidths using a Gaussian kernel. It illustrates that the choice of bandwidth controls the trade-off between bias and variance: while a relatively small bandwidth of 0.05 leads to a wiggly line that is clearly undersmoothed, a large bandwidth of 0.2 seems to lead to an oversmoothed graph (see discussion in section 8.2). Note that the marginal return to college is upward sloping independent of the choice of the bandwidth: Individuals facing higher (unobservable) borrowing rates, who have to be compensated by a higher $P(Z)$ to be made indifferent, have higher expected returns on the margin.

I calculate standard errors by performing a bootstrap over the two steps described in the previous section. Figure 6 displays the marginal return to college with 95% confidence intervals using a bandwidth of 0.15. Unfortunately error bands are wide in particularly for large values of

[28] Those individuals who already live less than 5km away from the closest university are given a value of 0km distance.

$P(Z)$ for which there are few data points.[29]

In the next section I will use these estimation results to perform policy experiments.

8.4 Results of the Policy Experiments

The goal of this section is twofold: First, I evaluate potential welfare implications of government policies, such as the introduction of a means-tested student loan program. Therefore I analyze the effect of a change in interest rate for poor (or poor and able) individuals and the effect of a change in direct costs –using distance to college–, by computing the change in college attendance rates as a result of the policy and by deriving the average "marginal" expected return of the individuals, who change their attendance decision in response. For the evaluation of policies it is crucial to derive the "marginal" return instead of just looking at the "average" return of a randomly selected individual, as the individuals, who will respond to policies are those "at the margin", while the "average" individual might be attending college anyways or might not be induced to attend and is thus not relevant for understanding the effect of the policy.

Second, I test whether the average "marginal" expected return is significantly larger than the average expected return of individuals attending college. This is comparable to Card's analysis of comparing IV coefficients to OLS coefficients (or better to the "Treatment on the Treated Effect"), but with subjective expectations of earnings instead of earnings realizations. Larger "marginal" returns indicate that individuals at the margin face higher unobserved costs (compare analysis in section 6).

In terms of the policy evaluation I estimate the "Policy Relevant Treatment Effect" ($PRTE$) for the policies of interest, which will be a weighted average of the marginal returns to college (MTE), where the weights depend on who will change participation as a response to the policy (see section 8.2).

The first policy I evaluate is the effect of decreasing the distance to the closest university, for example by building new universities in places that previously did not have higher education institutions. In section 7 I have shown that a change in distance to college affected poor high-return individuals most. Nevertheless, a change in costs only affects individuals at the margin, which I will take into account in this section. I perform the analysis by decreasing the distance to college by 10 kilometers (for different target groups), and determine the resulting distribution of the new propensity score, P^*. I then use the baseline distribution of P and the new distribution after the policy change of P^* to determine the relevant weights (see equation (17)) and determine a weighted average of $MTE(u)$, which gives me the $PRTE$ for this specific policy (see equation (16) and (17)).[30]

[29] Carneiro, Heckman and Vytlacil (2005) have the same problem of very wide confidence bands using the NLSY. The fact that my sample only contains relatively poor individuals all of which have a low probability of attending college is likely to aggravate the problem.

[30] I use the MTE that is based on a bandwidth of 0.15 and thus a rather conservative choice, as for smaller

A 10 kilometer-reduction in the distance to the closest university leads to an increase in college attendance of about 10% (2.3 percentage points), and to an average marginal expected return of 1.10 for those individuals induced to change their college attendance decision (see table 10). Decreasing the distance only for very poor individuals (less than 5,000 pesos per capita income), leads to a change in attendance of 3%, while those individuals who change college attendance have an average marginal expected return of 1.08. For poor and able individuals (per capita income less than 5,000 pesos and a GPA higher than the median), this policy would lead to a change in attendance of 2%, and an average marginal expected return of 1.11. These results imply that individuals at the margin have to be facing high unobserved costs to explain the fact that they did not attend college despite very high expected returns. For a full cost-and-benefit analysis of this policy the costs of building new universities would obviously have to be taken into account and it seems unlikely that this would be an efficient policy.

A more efficient policy could consist of the introduction of a governmental student loan program. Therefore, as a second policy experiment, I consider the effect of a decrease in the interest rate of poor (and able) individuals. A 10% change in the interest rate for very poor individuals leads to an average marginal return of 1.11 (the college attendance rate increases by about 50%, that is about 11 percentage points), while this change for poor and able individuals leads to an average marginal return of 1.14 (see table 10). In both cases, the average marginal return of individuals induced to change their college attendance decision is significantly higher than the average return of those individuals already attending college (0.72).

Again, for a full cost-and-benefit analysis one would have to take into account the costs of providing student loans, that is bureaucratic costs for setting in place an efficient system for giving out and recovering loans in addition to costs of interest.[31] If a large-scale policy is put in place, one would additionally have to take into account general equilibrium effects, in particular in terms of skill prices, but also in terms of the effects on development and growth of the country, as a more highly educated workforce might stimulate skill-biased technological change, which could even offset the wage depressing effects of a larger supply of college graduates. It could be interesting to analyze, whether individuals take into account the impact of a large-scale student loan or fellowship program on longer-run skill prices, that is to examine whether and how such a policy affects expectations of future earnings.

9 Conclusion

The goal of this paper has been to improve our understanding of both the causes and the implications of the steep income gradient in college attendance in Mexico by analyzing the determinants

bandwidths there is a stronger increase in the MTE in unobservables.

[31]Note that if poor credit-constrained individuals are extremely risk averse in terms of taking a loan, a government loan program might have no or very little effect, while a fellowship program could have much larger effects.

of college attendance using data on individuals' subjective expectations of earnings. In particular, I examined whether expected returns and perceived earnings risk –measures derived from data on each individual's future earnings distribution– are important determinants of higher-education decisions, and whether they help in explaining the strong correlation between parental income and children's college attendance.

Having data on individuals' expectations of earnings and perceived earnings risks is important, as not controlling for these measures could lead to a spurious positive correlation between parental income and college attendance. Since what matters for people's decisions is the perception of their own cognitive and social skills and how these skills affect their future earnings, these data ideally provide people's expectations conditional on their information sets at the time of the decision.

One of the paper's main findings is that expected returns to college and perceived risk of future earnings are important determinants of college attendance decisions, but that lower returns or higher risk are not sufficient to explain the poor's low college attendance rates. I also find that poor individuals require significantly higher expected returns to be induced to attend college, implying that they face significantly higher costs than individuals with wealthy parents. Furthermore, poor individuals with high expected returns are particularly responsive to changes in direct costs such as tuition, which is consistent with credit constraints playing an important role.

The results of my policy experiments indicate that there is a notable fraction of poor individuals with high expected returns, who are close to the margin of attending college, but do not attend. This suggests that credit constraints could be one of the driving forces of Mexico's large inequalities in access to higher education and low overall enrollment rates, which is consistent with Mexico's low government funding for student loans and fellowships for higher education. In this case the results of my policy experiments suggest that the introduction of a means-tested student loan program could lead to large welfare gains by removing obstacles to human capital accumulation and fostering Mexico's development and growth.

It is important to note that the evidence above is consistent with other factors also driving the poor's low college attendance rates, which would still imply scope for policy interventions, as long as some of the empirical patterns found were driven by credit constraints. Furthermore, government policies such as student loan programs might still be recommendable if the steep income gradient mostly reflects heterogeneity in time preferences, for example. This could be the case if there are externalities from college attendance and social returns are correlated with private returns, or if people have time-inconsistent preferences, e.g. they become more patient when getting older.

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10 Appendix A

Figure 1: College enrollment rates of 18 to 24 year old high school completers by parental income quartile (Mexican Family Life Survey, 2003).

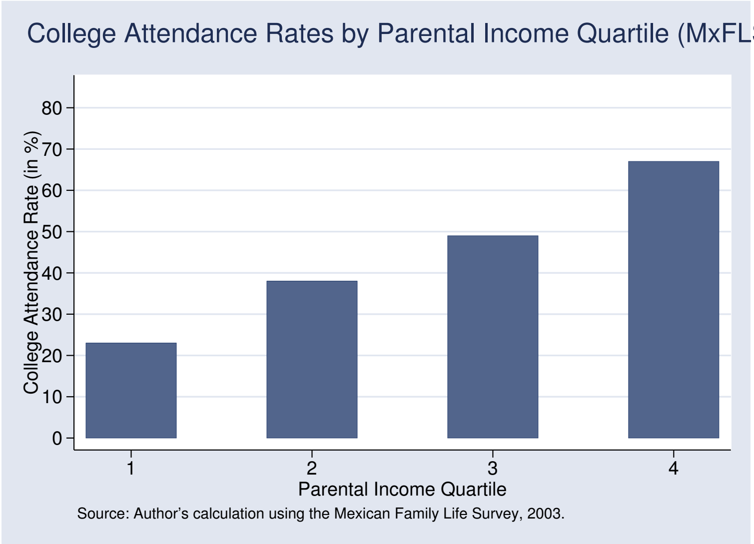

Figure 2: College enrollment rates of 18 to 24 year old high school completers by parental income quartile (Jovenes con Oportunidades Survey, 2005).

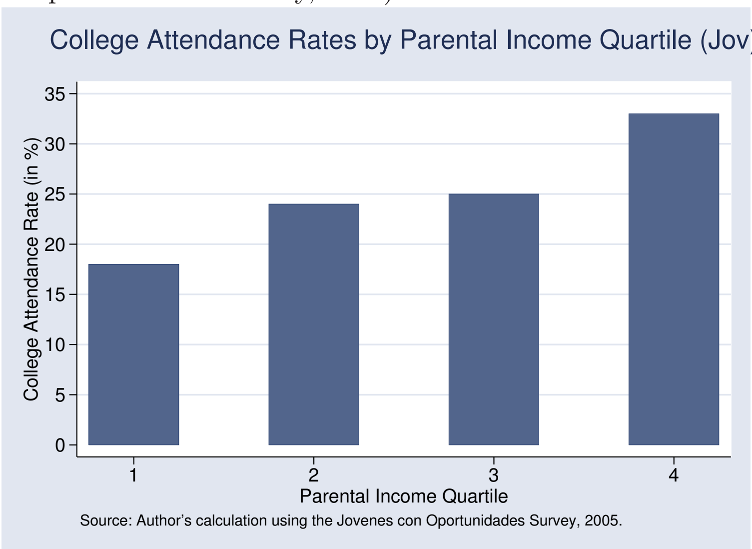

Figure 3: The triangular distribution of earnings

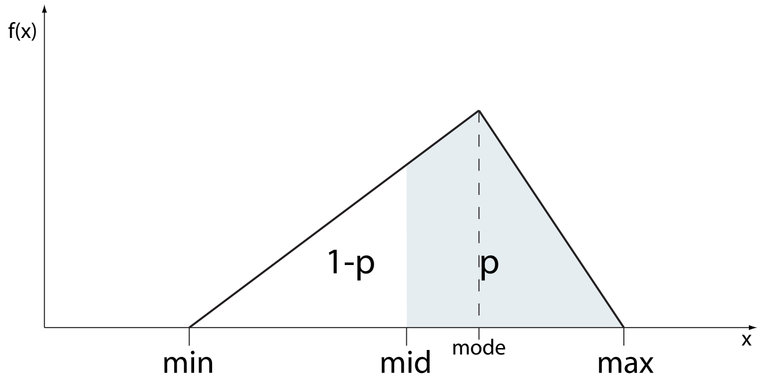

Figure 4: Predicted probability of attending college for high school graduates, who decided to attend college, and those, who stopped school after high school.

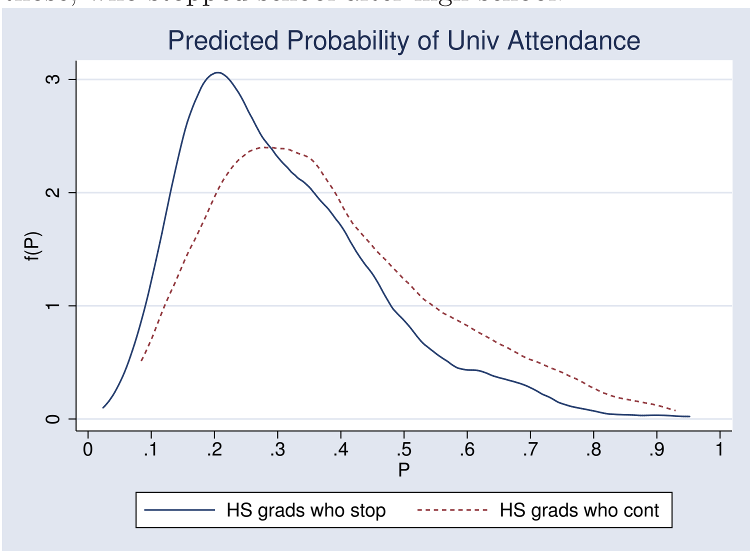

Figure 5: The Marginal Return to College ("MTE") conditional on different levels of unobserved costs (for different bandwidths).

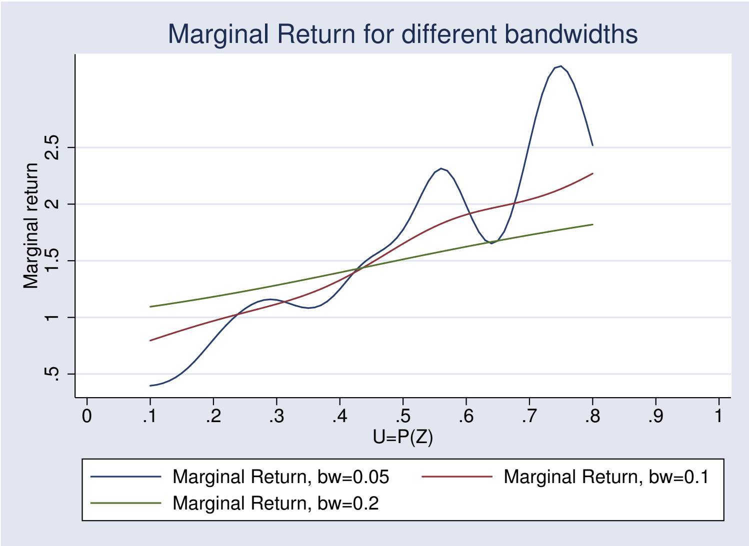

Figure 6: The Marginal Return to College ("MTE") conditional on different levels of unobserved costs with 95% C.I. bands for a bandwidth of 0.15.

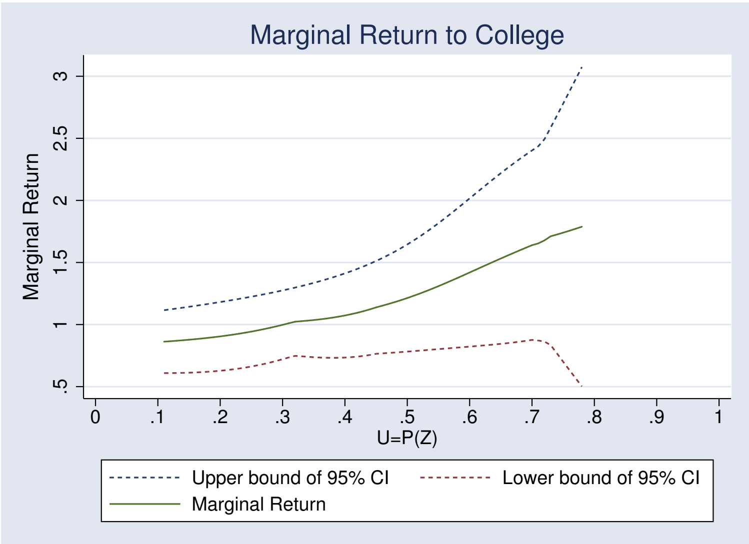

Figure 7: The Cumulative Distribution Function of Costs for Different Income Classes.

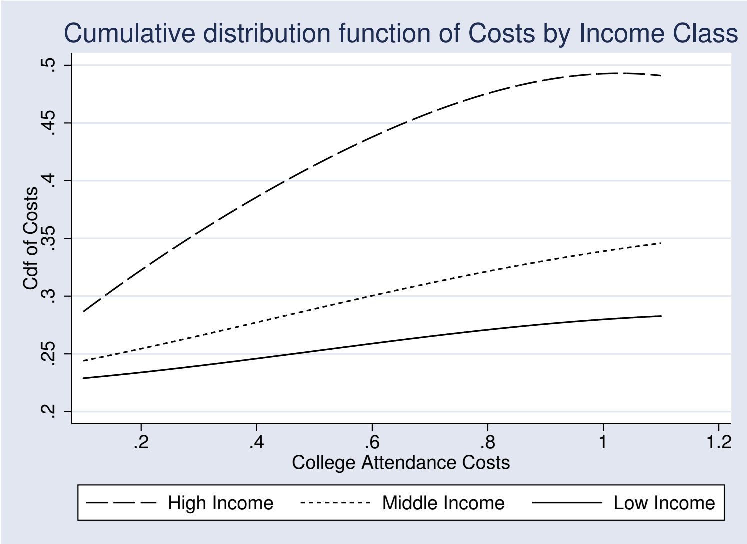

Figure 8: The Cumulative Distribution Function of Costs of Poor versus Rich Individuals with 95% Confidence Intervals.

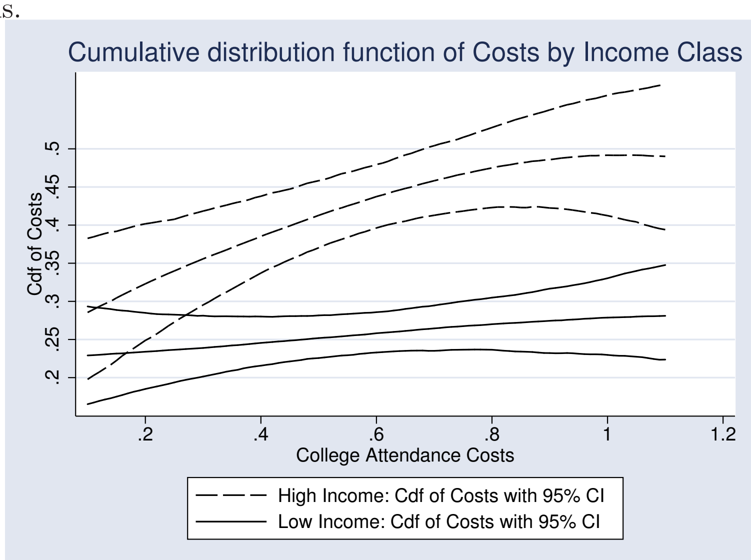

Figure 9: The Cumulative Distribution Function of Costs with 95% Confidence Intervals: for Different Income Classes.

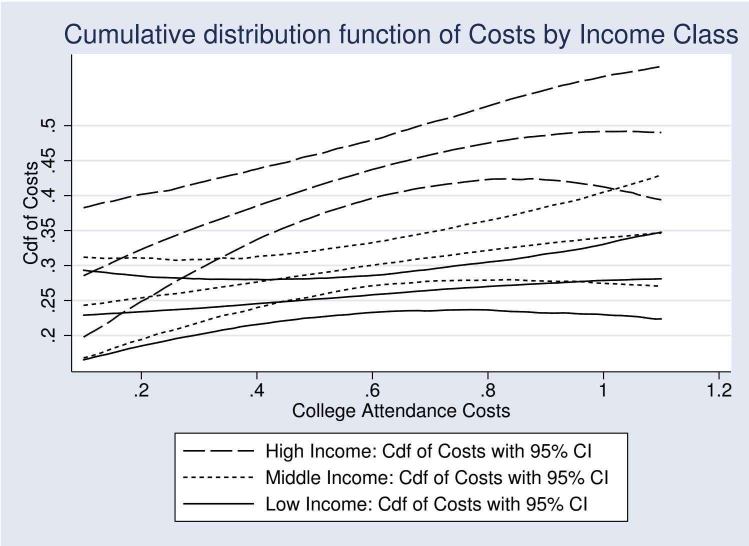

Figure 10: Pointwise Difference of the Cumulative Distribution Functions of Costs of Middle Income and Low Income Individuals with 5% and 10% Lower Bounds.

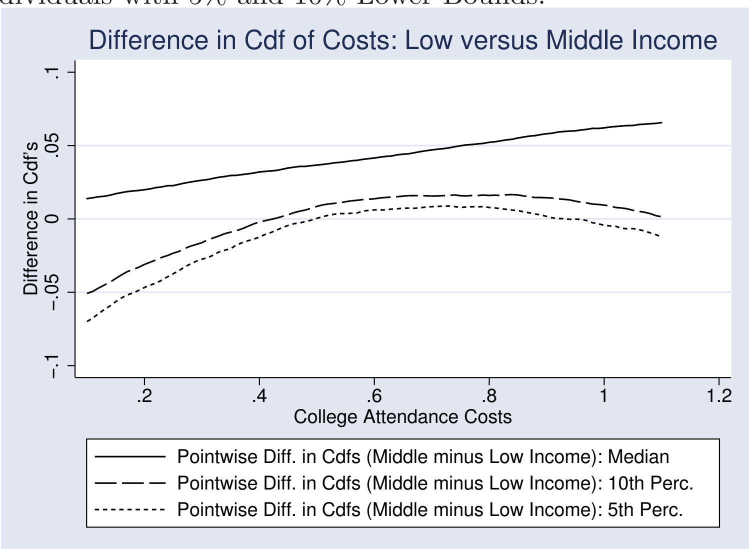

Table 1: Comparison of enrollment rates, fraction of poorest 40% in percent of the student population, fraction of GDP spend on higher education, fraction of expenditures on higher education on fellowships and student loans: Mexico, other Latin American countries, OECD and USA.

Countries Ranked by Per Cap GDP (PPP)	Enrollment in Higher Education in % of 18-24 Year Old	Fraction of Poorest 40% of 18-24 Year Old as % of Student Body	Expenditures on Higher Education in % of GDP	Spending on Fellowships and Loans in % of Exp. on Higher Educ	Beneficiaries of Student Loans (in % of students)
Brazil	16%	4%	1.5%	11.2%	6%
Colombia	23%	14%	1.7%	.	9%
Peru	29%	.	.	.	.
Mexico	**20%**	**8%**	**1.1%**	**6.2%**	**2%**
Chile	39%	16%	2.2%	34.8%	.
Argentina	37%	16%	1.1%	.	.
OECD average	56%	.	.	17.5%	.
USA	54%	20%	.	.	35%

Sources: World Bank (2005) for Enrollment and Fraction of Poorest 40%, OECD Indicators (2007) for Expenditures on Higher Education and on Spending on Fellowships and Loans. CIA World Factbook (2006) and IMF Country Ranking for Ranking of Per Capita GPD (PPP). For Beneficiaries of Student Loans: Ministery of Education, Brazil (2005); ICETEX, Colombia (2005); SOFES (2005), ICEES (2006), ICCET (2007) and Educafin (2007) in Mexico; US Office of Post-Secondary Education Website, 2006. Information not available indicated as ".".

Table 2: Summary statistics of important variables of the two groups of respondents.

Variable	Mother Respondent (M) Mean/(S.E.)	Adolescent Respondent (A) Mean/(S.E.)	Difference ((A)-(M)) Mean Difference (Sign.)
Attend College	35.8%	23.1%	-12.7%***
	(0.48)	(0.42)	
Female	50%	58%	8%***
	(0.50)	(0.49)	
Ability (GPA)	82.3	82.2	-0.1
	(10.34)	(7.16)	
Father's years of schooling	5.3	5.4	0.1
	(3.00)	(2.99)	
Per capita parental income	7493.25	7472.02	-21.23
	(7635.84)	(7909.00)	
Per capita household expenditures	8658.16	8283.25	-374.90*
	(5414.89)	(5539.60)	
Expected gross return	0.65	0.66	0.01
$(E(\ln Y_{\text{Col}}) - E(\ln Y_{\text{HS}}))$	(0.36)	(0.38)	
Distance to the closest university	27.40	24.16	-3.24***
	(23.35)	(22.72)	
Number of observations	2010	1670	

Table 3: Probit model for the college attendance decision.

Dependent Variable: Attend College	Model 1 Marg. Eff. (S.E.)	Model 2 Marg. Eff. (S.E.)	Model 3 Marg. Eff. (S.E.)
Expected Return to College	0.064***	0.059***	0.065***
	(0.021)	(0.021)	(0.021)
Prob of Work - HS	-0.020	-0.030	-0.047
	(0.053)	(0.054)	(0.054)
Prob of Work - College	0.110*	0.098	0.113*
	(0.062)	(0.063)	(0.063)
Var of Log Earn - HS	0.039	-0.430	-0.517
	(1.192)	(1.214)	(1.214)
Var of Log Earn - College	-2.975*	-2.669*	-2.434
	(1.557)	(1.556)	(1.560)
GPA - second tercile (d)		0.041**	0.037*
		(0.020)	(0.020)
GPA - top tercile (d)		0.144***	0.143***
		(0.019)	(0.019)
Father's educ - junior HS (d)		0.084***	0.063**
		(0.026)	(0.026)
Father's educ - HS (d)		0.174***	0.147***
		(0.052)	(0.052)
Father's educ - Univ (d)		0.472***	0.442***
		(0.085)	(0.090)
Per cap Income - 5 to 10k (d)			0.031*
			(0.019)
Per cap Income - more than 10k (d)			0.141***
			(0.023)
Closest university 20 to 40km (d)			-0.039**
			(0.018)
Closest university more than 40km (d)			-0.037*
			(0.021)
Tuition of closest university more than 750 pesos (d)			-0.071***
			(0.024)
State, Gender, Marital status dummies	Yes	Yes	Yes
Observations	3680	3680	3680
Log likelihood	-2216.924	-2162.110	-2135.614
P-value: Test of joint significance	0.000	0.000	0.000

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy variable from 0 to 1. Excl. categories: male, single, lowest GPA tercile, father's education primary or less, per capita parental income less than 5000 pesos, distance to closest university less than 20 kilometers, tuition costs less than 750 pesos.

Table 4: Probit model for the college attendance decision: Differential effect of distance to university for different per capita parental income categories.

Dependent Variable: Attend College	Model 4 Marg. Eff. (S.E.)	Model 5 Marg. Eff. (S.E.)
Univ 20 - 40km * Pcap Income < 5k (d)	-0.058**	-0.060**
	(0.028)	(0.028)
Univ 20 - 40km * Pcap Income 5 - 10k (d)	0.006	0.008
	(0.038)	(0.038)
Univ 20 - 40km * Pcap Income > 10k (d)	-0.039	-0.045
	(0.042)	(0.041)
Univ > 40km * Pcap Income < 5k (d)	-0.013	-0.018
	(0.030)	(0.029)
Univ > 40km * Pcap Income 5 - 10k (d)	-0.045	-0.055
	(0.039)	(0.038)
Univ > 40km * Pcap Income > 10k (d)	-0.052	-0.054
	(0.047)	(0.046)
Expected Return to College		0.070***
		(0.024)
Exp Log Earn - HS		0.006
		(0.020)
Prob of Work - HS		-0.043
		(0.054)
Prob of Work - College		0.105*
		(0.064)
Var of Log Earn - HS		-0.355
		(1.224)
Var of Log Earn - College		-2.488
		(1.573)
Per cap Income - 5 to 10k (d)	0.032	0.035
	(0.024)	(0.024)
Per cap Income - more than 10k (d)	0.156***	0.158***
	(0.029)	(0.029)
Controls for Ability and Father's educ	Yes	Yes
State, Gender, Marital status dummies	Yes	Yes
Observations	3680	3680
Log likelihood	-2156.287	-2146.800
P-value: Test of joint significance	0.000	0.000

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy variable from 0 to 1. Excl. categories: male, single, lowest GPA tercile, father's education primary or less, per capita parental income less than 5000 pesos, distance to closest university less than 20 kilometers.

Table 5: Probit model for college attendance decision: Differential effect of tuition costs for different per capita parental income categories.

Dependent Variable: Attend College	Model 6 Marg. Eff. (S.E.)	Model 7 Marg. Eff. (S.E.)
Tuition > 750 pesos * Pcap Income < 5k (d)	-0.069***	-0.075***
	(0.026)	(0.025)
Tuition > 750 pesos * Pcap Income 5 - 10k (d)	-0.040	-0.044
	(0.034)	(0.034)
Tuition > 750 pesos * Pcap Income > top (d)	0.081*	0.077*
	(0.046)	(0.046)
Univ 20 - 40km * Pcap Income < 5k (d)	-0.044	-0.044
	(0.029)	(0.029)
Univ 20 - 40km * Pcap Income 5 - 10k (d)	0.002	0.003
	(0.038)	(0.038)
Univ 20 - 40km * Pcap Income > 10k (d)	-0.034	-0.041
	(0.042)	(0.042)
Univ > 40km * Pcap Income < 5k (d)	-0.008	-0.013
	(0.030)	(0.030)
Univ > 40km * Pcap Income 5 - 10k (d)	-0.048	-0.059
	(0.038)	(0.038)
Univ > 40km * Pcap Income > 10k (d)	-0.046	-0.049
	(0.047)	(0.047)
Expected Return to College		0.073***
		(0.024)
Var of Log Earn - College		-2.653*
		(1.572)
Per cap Income - 5 to 10k (d)	0.037	0.041
	(0.028)	(0.029)
Per cap Income - more than 10k (d)	0.117***	0.119***
	(0.033)	(0.033)
Controls for Prob of Work, Exp and Var of Log Earn - HS	Yes	Yes
Controls for Ability and Father's educ	Yes	Yes
State, Gender, Marital status dummies	Yes	Yes
Observations	3680	3680
Log likelihood	-2149.967	-2139.878
P-value: Test of joint significance	0.000	0.000

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy from 0 to 1. Excl. categories: male, single, lowest GPA tercile, father's education primary or less, per capita parental income less than 5000 pesos, distance to closest university less than 20 kilometers, tuition costs less than 750 pesos.

Table 6: Probit model for the college attendance decision: Excess responsiveness of poor high-expected-return individuals to tuition costs.

Dependent Variable: Attend College	Model 8 Marg. Eff. (S.E.)	Model 9 Marg. Eff. (S.E.)
Tuition > 750 pesos * Pcap Income < 5k (d)	-0.076***	-0.030
	(0.025)	(0.037)
Tuition > 750 pesos * Pcap Income < 5k * Exp. Return high (d)		-0.089**
		(0.040)
Tuition > 750 pesos * Pcap Income 5 - 10k (d)	-0.041	-0.044
	(0.033)	(0.043)
Tuition > 750 pesos * Pcap Income 5 - 10k * Exp. Return high (d)		-0.003
		(0.054)
Tuition > 750 pesos * Pcap Income > 10k (d)	0.082*	0.057
	(0.046)	(0.066)
Tuition > 750 pesos * Pcap Income > 10k * Exp. Return high (d)		0.031
		(0.074)
Expected Return to College		0.084***
		(0.025)
Var of Log Earn - College		-2.690*
		(1.569)
Per cap Income - 5 to 10k (d)	0.033	0.034
	(0.023)	(0.023)
Per cap Income - more than 10k (d)	0.104***	0.104***
	(0.027)	(0.028)
Controls for Prob of Work, Exp and Var of Log Earn - HS	Yes	Yes
Controls for Ability and Father's educ	Yes	Yes
State, Gender, Marital status dummies	Yes	Yes
Observations	3680	3680
Log likelihood	-2152.201	-2140.357
P-value	0.000	0.000

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy from 0 to 1. Excl. categories: male, single, lowest GPA tercile, father's education primary or less, per capita parental income less than 5000 pesos, distance to closest university less than 20 kilometers, tuition costs less than 750 pesos.

Table 7: Maximum Likelihood Estimation of the participation equation as derived from the model of college attendance choice

Participation Equation		
Dependent Variable: Attend College	Coefficients	Std. Err.
Costs		
University Distance	-.0096	.003470***
University Distance Squared	.0001	.000036**
GPA of Junior High School	.0181	.004249***
Mother's Schooling	.0479	.014087***
Benefits		
Exp Gross Return to College	.2518	.108369**
Difference in Variances of College and HS Earnings	2.4630	1.299824*
(Exp Gross Return + Var Difference) Squared	-.1146	.060826*
Constant		
$-(1 + r)$	-10.2934	.487367***
Log-Likelihood	-550.8655	
Wald Chi Square (8)	26.98***	
N of observations	1057	

Signif. levels: *** 1%, ** 5%, * 10%

Table 8: Effect of changes in variables compared to the baseline case.

	Dist to Univ	Mother's schooling	GPA of Junior HS	Exp Gross Return to College	Prob of Attending	Diff
1	18.24	5	82	0.6213	0.2213	0.013
	13.24	5	82	0.61	0.2341	
2	18.24	5	82	0.6213	0.2213	0.018
	18.24	6	82	0.6213	0.2397	
3	18.24	5	82	0.6213	0.2213	0.007
	18.24	5	83	0.6213	0.2280	

For the baseline case all variables are evaluated at their median. One variable at a time is changed.

Table 9: Effect of changes in expected gross returns to college at different baseline cases.

	Dist to Univ	Mother's schooling	GPA of Junior HS	Exp Gross Return to College	Prob of Attending	Diff
4	18.24	5	82	0.6213	0.2213	0.010
	18.24	5	82	0.7213	0.2318	
5	13.24	5	82	0.6213	0.2213	0.024
	13.24	5	82	0.7213	0.2449	
6	18.24	6	82	0.6213	0.2396	0.011
	18.24	6	82	0.7213	0.2506	

For the first baseline case all variables are evaluated at their median. Then the effect of a change in expected returns is evaluated at different baselines.

Table 10: Results of Policy Experiments: Change in the College Attendance Rate, and the Average Marginal Expected Return compared to the Average Expected Return of the Individuals Attending College.

Policy Change	Individuals changing college attendance decision		Individuals attending college	P-Value of One-Sided Test
	Change in Overall Attendance Rate (in %)	**Marginal** Expected Return	**Average** Expected Return	
Decrease Interest Rate by 10%	80%	0.88	0.72	0.25
for very poor	50%	1.11	0.72	0.08
for very poor and able	32%	1.14	0.72	0.04
Decrease Dist by 10km	10%	1.10	0.72	0.11
for very poor	3%	1.08	0.72	0.15
for very poor and able	2%	1.11	0.72	0.08

11 Appendix B

11.1 Derivation of the Participation Equation from the Model of College Attendance Choice

In order to use the potential outcome equations (5) and the subjective expectation information (6), and rewrite the participation equation in terms of expected returns to college, I use the following approximation

$$E(Y_{ia}) \equiv E(e^{\ln Y_{ia}}) \cong e^{E(\ln Y_{ia})+0.5Var(\ln Y_{ia})} \tag{19}$$

and assume that $Var(\ln Y_{ia}^S) = (\sigma_i^S)^2$ for all a and $S = 0, 1$. Thus I can rewrite the expected present value of university earnings (analogously for high school earnings) as

$$\begin{aligned}
EPV(Y_i^1) &= \sum_{a=22}^{\infty} \frac{\exp(E(lnY_{ia}^1) + 0.5Var(lnY_i^1))}{(1+r)^{a-18}} \\
&= \sum_{a=22}^{\infty} \frac{\exp\left(\tilde{\alpha_1} + \beta_1' X_i + \gamma a + \theta_1' f_i + 0.5(\sigma_i^1)^2\right)}{(1+r)^{a-18}} \\
&= \frac{\exp\left(\tilde{\alpha_1} + \beta_1' X_i + \theta_1' f_i + 0.5(\sigma_i^1)^2\right)}{(1+r)^4} \cdot \left(\sum_{a=22}^{\infty} \frac{\exp(\gamma a)}{(1+r)^{a-22}} \right) \\
&= \frac{\exp\left(\tilde{\alpha_1} + \beta_1' X_i + \theta_1' f_i + 0.5(\sigma_i^1)^2\right)}{(1+r)^4} \cdot \exp(\gamma 22) \left(\frac{1}{1 - \left(\frac{\exp(\gamma)}{(1+r)}\right)} \right),
\end{aligned} \tag{20}$$

where I assume that $\exp(\gamma) < 1 + r$ to apply the rule for a geometric series. Analogously, I can derive the following expression for $EPV(Y_i^0)$

$$EPV(Y_i^0) = \exp\left(\tilde{\alpha_0} + \beta_0' X_i + \theta_0' f_i + 0.5(\sigma_i^0)^2\right) \cdot \exp(\gamma 18) \cdot \left(\frac{1+r}{1+r-\exp(\gamma)} \right). \tag{21}$$

Using expression (20) and (21), I can write the decision rule in the following way:

An individual decides to attend college if $EPV(Y_i^1) - EPV(Y_i^0) \geq C$, and thus if

$$\begin{aligned}
&\exp\left(\tilde{\alpha_1} + \beta_1' X_i + \theta_1' f_i + 0.5(\sigma_i^1)^2\right) \cdot \left(\frac{\exp(\gamma 22)}{(1+r)^4} \right) \cdot \left(\frac{1+r}{1+r-\exp(\gamma)} \right) \\
&- \left(\exp(\tilde{\alpha_0} + \beta_0' X_i + \theta_0' f_i + 0.5(\sigma_i^0)^2)\right) \cdot \exp(\gamma 18) \cdot \left(\frac{1+r}{1+r-\exp(\gamma)} \right) \geq C,
\end{aligned}$$

which I can rewrite in the following way

$$\begin{aligned}
\exp\left(\tilde{\alpha_1} + \beta_1' X_i + \gamma \cdot 25 + \theta_1' f_i + 0.5(\sigma_i^1)^2\right) - \left(\exp(\tilde{\alpha_0} + \beta_0' X_i + \gamma \cdot 25 + \theta_0' f_i + 0.5(\sigma_i^0)^2)\right) \cdot \\
\exp(-\gamma 4) \cdot (1+r)^4 \geq C \exp(\gamma 3)(1+r)^3(1+r-\exp(\gamma)).
\end{aligned}$$

Making use of the 'subjective' expectation information, this is equivalent to

$$\exp\left(E(\ln Y_{i25}^{1}) + 0.5(\sigma_i^1)^2\right) - \left(\exp(E(\ln Y_{i25}^{0}) + 0.5(\sigma_i^0)^2)\right) \cdot \exp(-\gamma 4) \cdot (1+r)^4 \\ \geq C\exp(\gamma 3)(1+r)^3(1+r-\exp(\gamma)). \tag{22}$$

In order to express the decision rule (22) in terms of expected gross returns to university and use the information on expected returns from 'subjective' expectations of earnings (see expression (7)), I use a Taylor series approximation of $\exp(B)$ around A, $\exp(B) = \exp(A)\sum_{j=0}^{\infty}\frac{(B-A)^j}{j!}$, to rewrite the decision rule, which has the form $\exp(B) - \exp(A)\cdot L \geq K$. Noting that in this context

$$\begin{aligned} B - A &= \left(E(\ln Y_{i25}^{1}) + 0.5(\sigma_i^1)^2\right) - \left(E(\ln Y_{i25}^{0}) + 0.5(\sigma_i^0)^2\right) \\ &= \rho_i + 0.5\left((\sigma_i^1)^2 - (\sigma_i^0)^2\right), \end{aligned}$$

I can write the decision rule as

$$\exp\left(E(\ln Y_{i25}^{0}) + 0.5(\sigma_i^0)^2\right) \cdot \left(\sum_{j=0}^{\infty}\frac{\left(\rho_i + 0.5\left((\sigma_i^1)^2 - (\sigma_i^0)^2\right)\right)^j}{j!}\right) \\ - \left(\exp(E(\ln Y_{i25}^{0}) + 0.5(\sigma_i^0)^2)\right) \cdot \exp(-\gamma 4) \cdot (1+r)^4 \geq C\exp(\gamma 3)(1+r)^3(1+r-\exp(\gamma))$$

and rearranging will lead to

$$\left(\sum_{j=0}^{\infty}\frac{\left(\rho_i + 0.5\left((\sigma_i^1)^2 - (\sigma_i^0)^2\right)\right)^j}{j!}\right) - \exp(-\gamma 4)\cdot(1+r)^4 - \frac{C\exp(\gamma 3)(1+r)^3(1+r-\exp(\gamma))}{\exp\left(E(\ln Y_{i25}^{0}) + 0.5(\sigma_i^0)^2\right)} \geq 0.$$

Thus using the 'subjective' expectation information, the latent variable model for attending university can be written as

$$\begin{aligned} S^* &= \left(\sum_{j=0}^{\infty}\frac{\left(\rho_i + 0.5\left((\sigma_i^1)^2 - (\sigma_i^0)^2\right)\right)^j}{j!}\right) \\ &\quad -(1+r)^4\left(\exp(-\gamma 4) + \frac{C\exp(\gamma 3)}{\exp\left(E(\ln Y_{i25}^{0}) + 0.5(\sigma_i^0)^2\right)}\right) \\ &\quad +(1+r)^3\left(\frac{C\exp(\gamma 4)}{\exp\left(E(\ln Y_{i25}^{0}) + 0.5(\sigma_i^0)^2\right)}\right) \\ S &= 1 \text{ if } S^* \geq 0 \\ S &= 0 \text{ otherwise,} \end{aligned} \tag{23}$$

where S is a binary variable indicating the treatment status.

11.2 Testable Predictions about Excess Responsiveness to Changes in Direct Costs

Making use of the participation equation for college attendance (23), the following results show that individuals who face a higher interest rate are more responsive to changes in direct costs.

$$\frac{\partial S^*}{\partial C} = \frac{-(1+r)^4\left(\exp(\gamma)\right)^3 + (1+r)^3\left(\exp(\gamma)\right)^4}{\exp\left(E(\ln Y^0_{i25}) + 0.5(\sigma^0_i)^2\right)} < 0$$

as $\exp(\gamma) < 1+r$ by assumption to apply the rule for geometric series (see previous section), and

$$\frac{\partial^2 S^*}{\partial C \partial r} = \frac{-4(1+r)^3\left(\exp(\gamma)\right)^3 + 3(1+r)^2\left(\exp(\gamma)\right)^4}{\exp\left(E(\ln Y^0_{i25}) + 0.5(\sigma^0_i)^2\right)} < 0 \qquad (24)$$

as $4(1+r) > 3\exp(\gamma)$.

Thus $\left|\frac{\partial S^*}{\partial C}\right|$ is increasing in r, that is individuals who face a higher interest rate are more responsive to changes in direct costs.

11.3 Derivation of the Marginal Return to College

Proof for deriving equation (15):

$$\begin{aligned}
E(U_1 - U_0|U_S \leq p) &= \int_{-\infty}^{\infty} (U_1 - U_0)\, f(U_1 - U_0|U_S \leq p) d(u_1 - u_0) \\
&= \int_{-\infty}^{\infty} (U_1 - U_0)\, \frac{\int_0^p f\left(U_1 - U_0, U_S\right) du_S}{Pr(U_S \leq p)} d(u_1 - u_0) \\
&= \int_{-\infty}^{\infty} (U_1 - U_0)\, \frac{\int_0^p f\left(U_1 - U_0|U_S\right) f(u_S) du_S}{p} d(u_1 - u_0) \\
&= \frac{1}{p}\int_0^p E\left(U_1 - U_0|U_S = u_S\right) du_S.
\end{aligned}$$

12 Appendix C: Robustness Checks

Figure 11: Comparison of the cross-sections of expected *high school* earnings of individuals in grade 12 ("young" cohort) with high school graduates, who already attend college or work ("old" cohort).

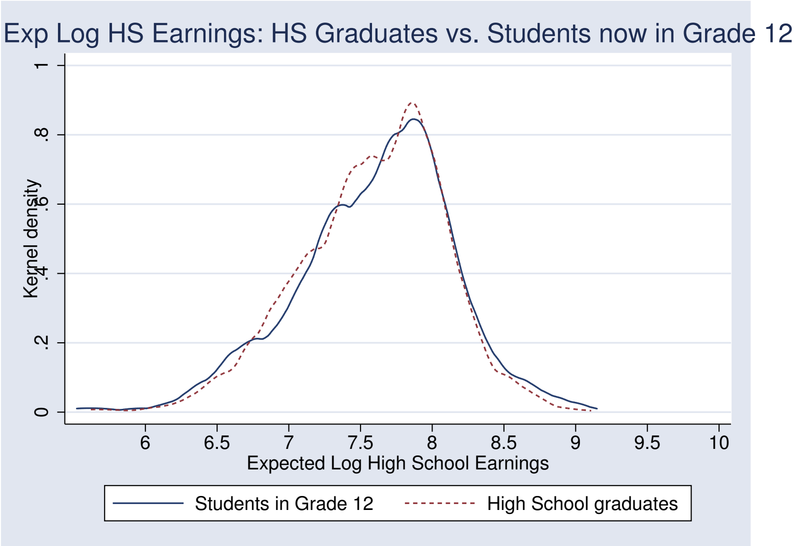

Figure 12: Comparison of the cross-sections of expected *college* earnings of individuals in grade 12 ("young" cohort) with high school graduates, who already attend college or work ("old" cohort).

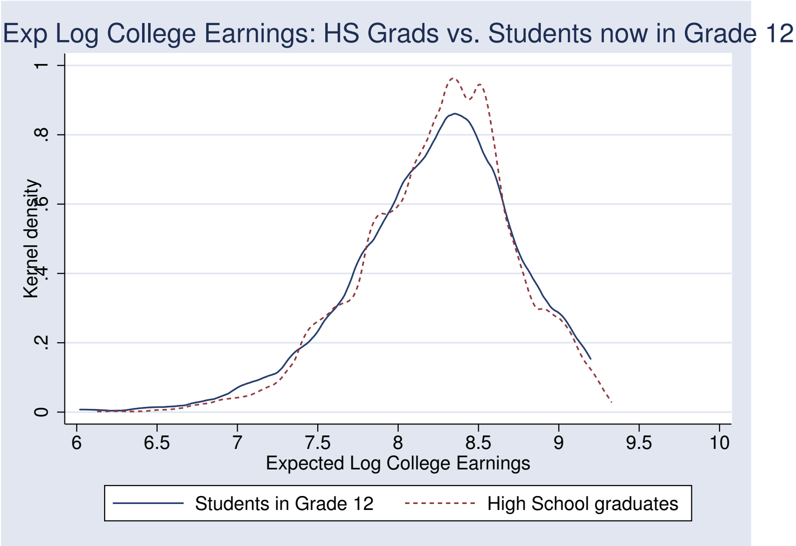

Figure 13: Scatter Plot and Nonparametric Regression of Expected Returns on Distance to University: Full Sample.

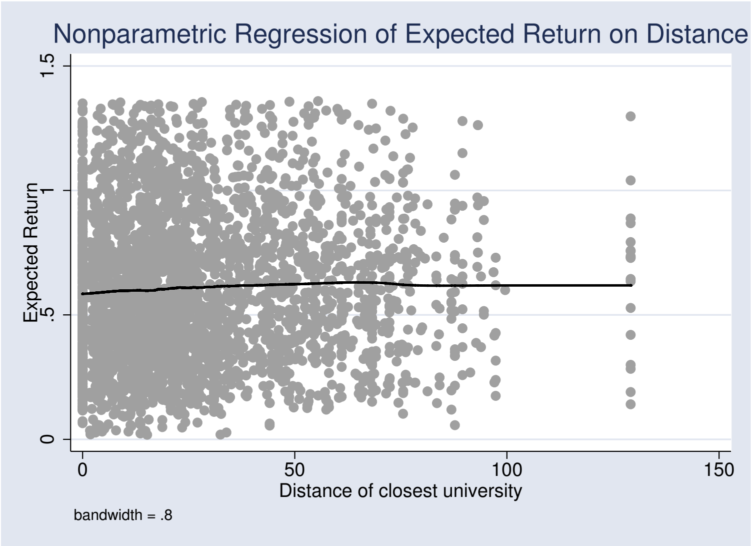

Figure 14: Scatter Plot and Nonparametric Regression of Expected Returns on Distance to University: Adolescent Sample.

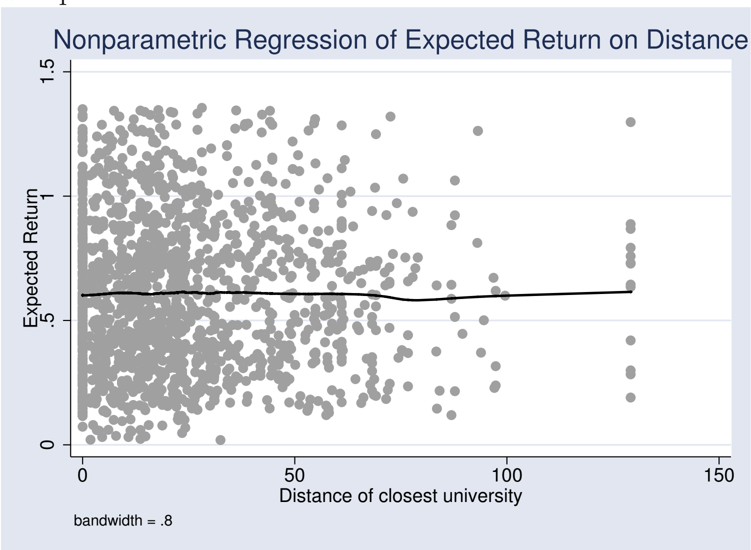

Table 11: Probit model for the college attendance decision correcting for sample selection: First stage results

Dep Var: Adolescent Respondent	Model 1	Model 2
	Marg. Eff./(S.E.)	Marg. Eff./(S.E.)
Interview Sunday (d)	0.117**	0.095
	(0.058)	(0.059)
Interview Thursday (d)	-0.070**	-0.078**
	(0.035)	(0.036)
Interview Saturday*Evening (d)	0.313***	0.344***
	(0.082)	(0.078)
Interview Sunday*Evening (d)	-0.202*	-0.194*
	(0.106)	(0.109)
Interview Week 40 (d)	0.162***	0.162***
	(0.058)	(0.059)
Interview Week 41 (d)	0.133***	0.159***
	(0.031)	(0.031)
Interview Week 42 (d)	0.098***	0.105***
	(0.027)	(0.028)
Interview Week 45 (d)	-0.052**	-0.064**
	(0.024)	(0.026)
Sex (d)		0.092***
		(0.017)
Married (d)		0.344***
		(0.068)
Civil Union (d)		0.400***
		(0.071)
GPA - second tercile (d)		0.066***
		(0.021)
GPA - top tercile (d)		-0.023
		(0.020)
Controls for Father's educ and Per cap Income	Not Sign	Not Sign
Controls for Distance to college and Tuition	Not Sign	Not Sign
State fixed effects	Yes	Yes
Observations	3680	3680
Log likelihood	-2483.362	-2376.194
P-value: Test of joint significance	0.000	0.000

Excl. categories: Interview on Monday, Interview in the morning, Interview in week 43, male, single, lowest GPA tercile, father's education primary or less, per capita income less than 5000 pesos, distance to college less than 20 kilometers, tuition less than 750 pesos.

Table 12: Probit model for the college attendance decision using the adolescent sample and correcting for sample selection.

Dependent Variable: Attend College	Model 1 Marg. Eff./(S.E.)	Model 2 Marg. Eff./(S.E.)	Model 3 Marg. Eff./(S.E.)
Expected Return to College	0.081**	0.077**	0.074**
	(0.032)	(0.033)	(0.032)
Prob of Work - HS	0.029	0.010	-0.009
	(0.083)	(0.084)	(0.073)
Prob of Work - College	0.043	0.030	0.032
	(0.096)	(0.097)	(0.084)
Var of Log Earn - HS	-2.264	-2.917	-2.750
	(1.803)	(1.927)	(1.784)
Var of Log Earn - College	-0.015	0.157	0.452
	(2.260)	(2.286)	(1.995)
GPA - second tercile (d)		0.044	0.034
		(0.031)	(0.028)
GPA - top tercile (d)		0.170***	0.149***
		(0.031)	(0.040)
Father's educ - junior HS (d)		0.100**	0.068*
		(0.040)	(0.039)
Father's educ - HS (d)		0.191***	0.131*
		(0.074)	(0.073)
Father's educ - Univ (d)		0.524***	0.575***
		(0.125)	(0.147)
Per cap Income - 5 to 10k (d)			0.040
			(0.029)
Per cap Income - more than 10k (d)			0.105***
			(0.040)
Closest university 20 to 40km (d)			-0.066**
			(0.027)
Closest university more than 40km (d)			-0.096***
			(0.031)
Tuition of closest university more than 750 pesos (d)			-0.097**
			(0.041)
State, Gender, Marital status dummies	Yes	Yes	Yes
Observations	3680	3680	3680
Log likelihood	-3290.394	-3261.734	-3229.325
P-value: Test of joint significance	0.001	0.000	0.000
Sample sel: Correlation between error terms	-0.534	-0.351	0.002
P-value of LR test of indep eqns	0.057	0.299	0.995

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy variable from 0 to 1.

Excl. categories: male, single, lowest GPA tercile, father's education primary or less, per capita parental income less than 5000 pesos, distance to closest university less than 20 kilometers, tuition costs less than 750 pesos.

Table 13: Probit model for the college attendance decision with sample selection correction: Differential effect of distance to university for different per capita parental income categories.

Dependent Variable: Attend College	Model 4	Model 5
	Marg. Eff./(S.E.)	Marg. Eff./(S.E.)
Univ 20 - 40km * Pcap Income < 5k (d)	-0.063**	-0.063**
	(0.030)	(0.029)
Univ 20 - 40km * Pcap Income 5 - 10k (d)	-0.041	-0.043
	(0.036)	(0.035)
Univ 20 - 40km * Pcap Income > 10k (d)	0.017	0.011
	(0.049)	(0.046)
Univ > 40km * Pcap Income < 5k (d)	-0.043	-0.044
	(0.029)	(0.028)
Univ > 40km * Pcap Income 5 - 10k (d)	-0.095***	-0.096***
	(0.037)	(0.035)
Univ > 40km * Pcap Income > 10k (d)	-0.033	-0.033
	(0.048)	(0.045)
Expected Return to College		0.053*
		(0.028)
Exp Log Earn - HS		-0.010
		(0.020)
Prob of Work - HS		-0.003
		(0.055)
Prob of Work - College		0.044
		(0.065)
Var of Log Earn - HS		-2.047
		(1.375)
Var of Log Earn - College		0.154
		(1.513)
Per cap Income - 5 to 10k (d)	0.061*	0.061*
	(0.032)	(0.031)
Per cap Income - more than 10k (d)	0.095**	0.092**
	(0.041)	(0.041)
Controls for Ability and Father's educ	Yes	Yes
State, Gender, Marital status dummies	Yes	Yes
Observations	3680	3680
Log likelihood	-3253.562	-3247.898
P-value: Test of joint significance	0.000	0.000
Sample sel: correlation between error terms	0.282	0.328
P-value of LR test of indep eqns	0.308	0.243

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy variable from 0 to 1. Excl. categories: male, single, lowest GPA tercile, father's education primary or less, per capita parental income less than 5000 pesos, distance to closest university less than 20 kilometers.

Table 14: Probit model for college attendance decision with sample selection correction: Differential effect of tuition costs for different per capita parental income categories.

Dependent Variable: Attend College	Model 6	Model 7
	Marg. Eff./(S.E.)	Marg. Eff./(S.E.)
Tuition > 750 pesos * Pcap Income < 5k (d)	-0.012	-0.016
	(0.028)	(0.027)
Tuition > 750 pesos * Pcap Income 5 - 10k (d)	-0.019	-0.022
	(0.036)	(0.035)
Tuition > 750 pesos * Pcap Income > top (d)	0.065	0.061
	(0.054)	(0.052)
Univ 20 - 40km * Pcap Income < 5k (d)	-0.060**	-0.059**
	(0.030)	(0.029)
Univ 20 - 40km * Pcap Income 5 - 10k (d)	-0.044	-0.046
	(0.036)	(0.035)
Univ 20 - 40km * Pcap Income > 10k (d)	0.024	0.018
	(0.050)	(0.047)
Univ > 40km * Pcap Income < 5k (d)	-0.042	-0.042
	(0.029)	(0.028)
Univ > 40km * Pcap Income 5 - 10k (d)	-0.094**	-0.096***
	(0.037)	(0.036)
Univ > 40km * Pcap Income > 10k (d)	-0.032	-0.032
	(0.048)	(0.046)
Expected Return to College		0.052*
		(0.028)
Per cap Income - 5 to 10k (d)	0.066*	0.068*
	(0.039)	(0.039)
Per cap Income - more than 10k (d)	0.064	0.063
	(0.043)	(0.042)
Controls for Prob of Work, Exp and Var of Log Earn - HS	Yes	Yes
Controls for Ability and Father's educ	Yes	Yes
State, Gender, Marital status dummies	Yes	Yes
Observations	3680	3680
Log likelihood	-3252.215	-3246.406
P-value: Test of joint significance	0.000	0.000
Sample sel: correlation between error terms	0.289	0.331
P-value of LR test of indep eqns	0.303	0.247

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy from 0 to 1. Excl. categories: male, single, lowest GPA tercile, father's education primary or less, per capita parental income less than 5000 pesos, distance to closest university less than 20 kilometers, tuition costs less than 750 pesos.

Table 15: Probit model for college attendance decision with sample selection correction: Differential effect of tuition costs for poor high expected return individuals.

Dependent Variable: Attend College	Model 8	Model 9
	Marg. Eff./(S.E.)	Marg. Eff./(S.E.)
Tuition > 750 pesos * Pcap Income < 5k (d)	-0.030	0.037
	(0.031)	(0.045)
Tuition > 750 pesos * Pcap Income < 5k * Exp Return high (d)		-0.110**
		(0.044)
Tuition > 750 pesos * Pcap Income 5 - 10k (d)	-0.022	-0.052
	(0.043)	(0.051)
Tuition > 750 pesos * Pcap Income 5 - 10k * Exp Return high (d)		0.054
		(0.075)
Tuition > 750 pesos * Pcap Income > top (d)	0.068	0.031
	(0.060)	(0.076)
Tuition > 750 pesos * Pcap Income > 10k * Exp Return high (d)		0.050
		(0.090)
Expected Return to College		0.075**
		(0.035)
Per cap Income - 5 to 10k (d)	0.056	0.055
	(0.035)	(0.035)
Per cap Income - more than 10k (d)	0.096**	0.093**
	(0.042)	(0.041)
Controls for Prob of Work, Exp and Var of Log Earn - HS	Yes	Yes
Controls for Ability and Father's educ	Yes	Yes
State, Gender, Marital status dummies	Yes	Yes
Observations	3680	3680
Log likelihood	-3247.959	-3238.761
P-value: Test of joint significance	0.000	0.000
Sample sel: correlation between error terms	0.092	0.131
P-value of LR test of indep eqns	0.751	0.649

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy from 0 to 1.
Excl. categories: male, single, lowest GPA tercile, father's education primary or less, per capita parental income less than 5000 pesos, distance to closest university less than 20 kilometers, tuition costs less than 750 pesos.

Table 16: Probit model for college attendance decision using the full sample: Differential effect of tuition costs for different quartiles of parental income and wealth.

Dependent Variable: Attend College	Model 1 Marg. Eff./(S.E.)	Model 2 Marg. Eff./(S.E.)
Tuition > 750 pesos * Par income/wealth quart 1 (d)	-0.116***	-0.047
	(0.028)	(0.046)
Tuition > 750 pesos * Par income/wealth quart 1 * Exp Return high (d)		-0.128***
		(0.048)
Tuition > 750 pesos * Par income/wealth quart 2 (d)	-0.032	0.000
	(0.040)	(0.054)
Tuition > 750 pesos * Par income/wealth quart 2 * Exp Return high (d)		-0.057
		(0.055)
Tuition > 750 pesos * Par income/wealth quart 3 (d)	-0.059	-0.041
	(0.038)	(0.053)
Tuition > 750 pesos * Par income/wealth quart 3 * Exp Return high (d)		-0.034
		(0.061)
Tuition > 750 pesos * Par income/wealth quart 4 (d)	0.072	0.058
	(0.045)	(0.064)
Tuition > 750 pesos * Par income/wealth quart 4 * Exp Return high (d)		0.019
		(0.070)
Expected Return to College	0.069***	0.085***
	(0.024)	(0.025)
Var of Log Earn - College	-2.859*	-2.901*
	(1.573)	(1.573)
Par income/wealth quart 2 (d)	-0.006	-0.006
	(0.028)	(0.028)
Par income/wealth quart 3 (d)	0.050*	0.050*
	(0.028)	(0.028)
Par income/wealth quart 4 (d)	0.082***	0.083***
	(0.028)	(0.028)
Controls for Prob of Work, Exp and Var of Log Earn - HS	Yes	Yes
Controls for Ability and Father's educ	Yes	Yes
State, Gender, Marital status dummies	Yes	Yes
Observations	3680	3680
Log likelihood	-2145.797	-2142.660
P-value: Test of joint significance	0.000	0.000

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy from 0 to 1.
Excl. categories: male, single, lowest GPA tercile, father's education primary or less, lowest parental income/ wealth quartile, distance to closest university less than 20 kilometers, tuition costs less than 750 pesos.

Table 17: Expected Returns: Correlation with Distance to College for Full Sample and Adolescent Sample controlling for Self-Selection.

Dependent Variable: Expected Return	Full Sample Coeff./(S.E.)	Adolescent Sample Coeff./(S.E.)
Distance to closest university	0.002***	0.001
	(0.001)	(0.001)
Distance squared	-0.000	-0.000
	(0.000)	(0.000)
GPA - second tercile	0.012	0.044**
	(0.012)	(0.020)
GPA - top tercile	0.032***	0.069***
	(0.012)	(0.019)
Father's educ - junior HS	0.010	0.025
	(0.016)	(0.025)
Father's educ - HS	0.060*	0.084*
	(0.031)	(0.045)
Father's educ - Univ	-0.006	-0.126
	(0.060)	(0.115)
Per cap Income - 5 to 10k	-0.005	-0.004
	(0.012)	(0.019)
Per cap Income - more than 10k	0.016	0.005
	(0.014)	(0.021)
State, gender, marital status dummies	Yes	Yes
Observations (censored)	3493	3493 (1916)
Lambda		-0.028
S.E. of Lambda		0.054

Notes: * p<0.1 ** p<0.05 *** p<0.01. (d) for discrete change of dummy variable from 0 to 1. Excl. categories: male, single, lowest GPA tercile, father's education primary or less, per capita expenditures less than 5000 pesos, and per capita income less than 5000 pesos, no university in municipality of residence.