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

Katja Maria Kaufmann*

Abstract

Differences in college enrollment rates between poor and rich students are a prevalent phenomenon, but particularly striking in Latin America. The literature suggests explanations such as differences in "college preparedness" on the one hand, in that poor students lack skills that enable them to benefit from college, and "credit constraints" on the other hand. One explanation that has been neglected in this analysis consists of differences in information sets between the poor and the rich –for example about career opportunities– translating into different perceptions of individual returns to college. Data on people's subjective expectations of returns allow to take this factor into account and to directly address the following identification problem: conditional on their information sets poor people might expect low returns and thus decide not to attend. Or they might face high (unobserved) costs that prevent them from attending despite high expected returns. Conventional approaches rely on strong assumptions about people's information sets and about how they form expectations to address this identification problem.

Data on people's subjective expectations of returns as well as on their schooling decisions allow me to directly estimate and compare cost distributions of poor and rich individuals. I find that poor individuals require significantly higher expected returns to be induced to attend college, implying that they face higher costs than individuals with wealthy parents. I then test predictions of a 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, which is consistent with credit constraints playing an important role. Evaluating potential welfare implications by applying the Local Instrumental Variables approach of Heckman and Vytlacil (2005) to my model, I find that a sizeable fraction of poor individuals would change their decision in response to a reduction in direct costs. Individuals at the margin have expected returns that are as high or higher than the individuals already attending college, suggesting that government policies such as fellowship programs could lead to large welfare gains.

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

Keywords: Schooling Choice, Credit Constraints, Subjective Expectations, Marginal Returns to Schooling, Local Instrumental Variables Approach, Mexico.

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1 Introduction

Differences in college enrollment rates between poor and rich students are a prevalent phenomenon, but particularly striking in Latin America. 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. This is low even compared to other Latin American countries. The richest 20% on the other hand constitute 60% of the student body. In addition overall college enrollment is particularly low in Mexico.[1] These empirical facts might reflect an important welfare loss if returns to education are high, but poor people cannot take advantage of them because they are credit constrained.

When examining reasons for low school attendance among the poor, researchers face the following identification problem: On the one hand poor people might expect particularly low returns to schooling –due for example to lower cognitive skills or perceptions of limited career opportunities even with a college degree–, and thus decide not to attend. On the other hand they might face high attendance costs that prevent them from attending despite high expected returns. To address this identification problem, I use data on people's subjective expectations of their idiosyncratic returns to college as well as on their college attendance choice.

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, who are 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), Cameron and Heckman (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

[1] A strong correlation between children's educational attainment and parental resources has been documented for many 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. In Appendix C, I compare several Latin American countries and the US and OECD in terms of attendance rates, inequality in access to higher education, and availability of fellowship and student loan programs (see Table 8) and I give detailed background information on costs and financing of college attendance in Mexico.

[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.

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 the attendance decision. I cannot show this in my data for the case of Mexico. Nevertheless, it would be premature to conclude that this proves the importance of credit constraints.

This paper contributes to the literature on credit constraints by taking into account one potentially important difference between the poor and the rich that has been neglected by previous studies: there might be important differences in information sets between rich and poor students, for example about career opportunities with a college degree, which are unobserved by the researcher. These differences in information sets could translate into differences in expected returns (and risk perceptions) between the poor and the rich and could thus affect their decision to attend college.

I address this concern directly by using data on each individual's (subjective) expectations of future earnings for both high school and college as the highest degree.[3] Since what matters for the college attendance decision is each individual's perception of her own skills and how these skills (and other individual or family characteristics) 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.

Consider the conventional model of educational choices under uncertainty. In such a model, the decision to attend college depends on expected returns (and risk) from investing in college education, preferences, and potentially credit constraints. All these determinants are at least partly unobserved by the econometrician, posing an important identification problem (see, e.g., Manski (2004) and Cunha and Heckman (2006)).

The existing "credit constraints" literature derives measures of earnings expectations using earnings realizations.[4] This approach requires strong (and implausible) assumptions about individuals' information sets as well as about the mechanisms behind how people form expectations. 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

[3]The seminal paper eliciting subjective expectations of earnings for different schooling degrees is by Dominitz and Manski (1996). They illustrate for a small sample of Wisconsin high school and college students that people are willing and able to answer subjective expectations questions in a meaningful way, but do not analyze the link between earnings expectations and investment into schooling.

[4]Stinebrickner and Stinebrickner (2008) provide an alternative approach for investigating the importance of credit constraints in college drop-out decisions in the US. They make use of a unique longitudinal data set at Berea college, where 50% of students drop out despite full tuition and room and board subsidies. They show that drop-out rates would remain high even if credit constraints were removed entirely, that is when excluding students who would like to borrow to smooth consumption during studying but cannot.

have self-selected into schooling.

This paper shows formally how data on people's subjective expectations allow to relax strong assumptions on information sets and expectation formation, and how these data can be used in the estimation of a school choice model. Data on subjective expectations permit to take into account another potentially important determinant of college attendance, that 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. 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)).[5] Data on subjective expectations can be used to derive a measure of perceived risk that does not confound heterogeneity and "true" risk.

The first finding of this paper is that even though expected returns to college are important determinants of college attendance decisions, they are not sufficient to explain the differences in attendance rates between poor and rich students.[6] Data on people's expected returns and on their schooling decisions allow me to directly estimate and compare cost distributions of poor and rich individuals. I find that poor individuals require significantly higher expected returns to be induced to attend college, implying that they face higher costs than individuals with wealthy parents.

To understand the role of different cost components, I test predictions of a 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 are particularly responsive to changes in direct costs such as tuition, which is consistent with them facing a higher interest rate. Furthermore, this result is entirely driven by poor high-expected-return individuals, as they are the ones close to the margin of indifference and thus affected by changes in direct costs.

Evaluating potential welfare implications by applying the Local Instrumental Variables approach of Heckman and Vytlacil (2005) to my model, I find that a sizeable fraction of poor individuals would change their decision and attend in response to a reduction in direct costs. Individuals at

[5] Exceptions are 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.

[6] The following related papers also find that "perceived" returns to schooling matter for people's schooling decisions: Jensen (forthcoming) finds that the students in his sample of 8th graders in the Dominican Republic significantly underestimate returns to schooling. Informing a random subset of them about higher measured returns leads to a significant increase in perceived returns and in attained years of schooling among these students. Nguyen (2008) finds that informing a random subset of a sample of students in Madagascar about high returns to schooling increases their attendance rates and their test scores. Attanasio and Kaufmann (2009) address two complementary issues concerning the link between schooling choice and expectations (using the same data as this paper). In addition to expected returns they also take into account perceived earnings and employment risk. Second, they have data on mothers' expectations about earnings of their children as well as adolescents' own expectations and can thus shed light on whose expectations matter for educational choices. They provide some preliminary evidence on the existence of credit constraints based on the argument that credit constraints would break the link between expected returns (or risk perceptions) and schooling decisions. A reduced-form regression shows that the likelihood of school attendance increases in expected returns for the rich, but not for poor students.

the margin have expected returns that are as high or higher than the ones of individuals already attending college, which indicates that they might be prevented from attending because they face high borrowing costs.

The findings of this paper suggest that credit constraints are 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 counterfactual policy experiments point to the possibility of large welfare gains from introducing a governmental fellowship program 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. One alternative explanation could be heterogeneity in time preferences. Even if none of the empirical patterns found in the data were driven by credit constraints, high expected returns of a sizable fraction of non-attenders could still justify government policies, 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.

2 Model of College Attendance Choice

In the Mexican context parental income and wealth remain strong predictors of children's likelihood to attend college even after controlling for cognitive skills and family background that proxy for returns to college in conventional approaches. Nevertheless it would be premature to conclude that this is evidence of credit constraints. As discussed above, the literature on credit constraints has neglected potential differences in information sets between poor and rich students that could translate into differences in expected returns and thereby affect the decision to attend college. For example, a student from a poor background might think (and rationally so) that even with a college degree she will not be hired for certain jobs that someone from a richer background with "connections" will be hired for (even if both students have the same level of skills). Thus parental connections can affect (expected) returns, but are usually not in the information set of the researcher, while they are in the one of the individual affecting her expectations and indirectly her decision to attend college. Neglecting these factors can lead to wrong conclusions about what is driving college attendance decisions. Data on people's subjective expectations of returns to college can address this concern directly.

I use a simple model of college attendance to show formally how direct information on people's subjective expectations can relax strong assumptions of conventional approaches about people's information sets. The model enables me to derive testable implications of credit constraints and to perform counterfactual policy experiments, such as evaluating the welfare implications of a governmental fellowship program.

I model the college attendance decision of a high school graduate at age 18 as follows: The high school graduate decides to enroll in college ($S = 1$), if the expected present value of earnings when enrolling in college –conditional on the information she has at age 18– ($EPV_{18}(S = 1)$) minus the expected present value of high school earnings –again conditional on the information she has at age 18– ($EPV_{18}(S = 0)$) is larger than the costs of attending college (direct costs C_i, such as tuition, transportation, room and board –if necessary– and monetized psychological costs or benefits):

$$S_i^* = EPV_{18}(S = 1) - EPV_{18}(S = 0) - C_i$$

If the individual decides to enroll in college, she will complete college with probability p_i^C and receive the expected present value of college earnings, $EPV_{18}(Y_i^1)$. If she drops out (D), she receives $EPV_{18}(Y_i^D)$, which I assume to be equal to the expected present value of high school earnings $EPV_{18}(Y_i^0)$.

$$\begin{aligned} S_i^* &= p_i^C EPV_{18}(Y_i^1) + (1 - p_i^C) EPV_{18}(Y_i^0) - EPV_{18}(Y_i^0) - C_i \\ &= p_i^C \sum_{a=22}^{A} \frac{p_{ia}^{W1} E_{18}(Y_{ia}^1)}{(1 + r_i)^{a-18}} - p_i^C \sum_{a=18}^{A} \frac{p_{ia}^{W0} E_{18}(Y_{ia}^0)}{(1 + r_i)^{a-18}} - C_i \geq 0, \end{aligned} \tag{1}$$

where i denotes the individual, a the age of the individual, A the age at retirement. $E_{18}(Y_{ia}^1)$ represents expected earnings with a college degree, $E_{18}(Y_{ia}^0)$ expected high school earnings, p_{ia}^{W1} and p_{ia}^{W0} represent the probabilities of being employed with college and high school degree and r_i the interest rate that individual i faces. It is important to stress that the expectations should be taken conditional on the information that the individual has at the time of making the decision. This is obviously also true for the perceived probabilities of working and completing college, which have been simplified to p_{ia}^{W1}, p_{ia}^{W0} and p_i^C for notational convenience.

Before discussing in detail the assumptions of this model, I first show formally how data on subjective expectations can be used in a model of school choice and how this compares to conventional approaches using earnings realizations. In particular I show how these data can be used to relax strong and unrealistic assumptions on people's information sets and on how they form expectations.

Assume that the economic model generating the data for the two potential outcomes, that is for earnings with a high school degree ($j = 0$) and for earnings with a college degree ($j = 1$), is of the following form ("Generalized Roy Model"):

$$\begin{aligned}\ln Y_{ia}^j &= \alpha_j + \beta_j' X_i + \gamma_j p_{ia}^{Wj}(a - s^j - 6) + U_{ia}^j \\ &= \alpha_j + \beta_j' X_i + \gamma_j p_{ia}^{Wj}(a - s^j - 6) + \theta_j' f_i + \epsilon_{ia}^j,\end{aligned} \tag{2}$$

over the whole life-cycle, $a = 18, ..., A$. In this model a high school degree implies 12 years of schooling ($s^0 = 12$), and a college degree implies 16 years of schooling ($s^1 = 16$). In terms of observable variables a labels age, A age at retirement and X denotes other observable time-invariant variables. $(a - s^j - 6)$ represents potential labor market experience, which is multiplied by the perceived probability of being employed, p_{ia}^{Wj} for $(j = 0, 1)$, to capture that the individual will work and gain experience only part of the year.

U^j represents the unobservables in the potential outcome equation, which are unobserved from the perspective of the researcher. They are composed of a part that is anticipated by the individual 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 $j = 0, 1$. f_i is the individual's skill vector which captures cognitive and social skills (and any other characteristics of the individual and family that affect future earnings), and θ_j is a vector of (beliefs over future) skill prices. Both f_i and θ_j are in the information set of the individual, while they are –at least in part– unobservable for the researcher.[7] In the conventional approach using earnings realizations $\theta_j' f_i$ is unobserved, while $\theta_j' f_i$ is implicitly 'observed' in the approach using data on subjective expectations of earnings. For each individual I have data on her expectations of earnings for age a for both potential schooling degrees, that is on the left-hand sides of the following equations:

$$\begin{aligned}E_{18}(\ln Y_{ia}^0) &= \alpha_0 + \beta_0' X_i + \gamma_0 p_{ia}^{W0}(a - 18) + \theta_0' f_i \\ E_{18}(\ln Y_{ia}^1) &= \alpha_1 + \beta_1' X_i + \gamma_1 p_{ia}^{W1}(a - 22) + \theta_1' f_i,\end{aligned} \tag{3}$$

Data on subjective expectations allow me to relax the assumption of rational expectations. Beliefs about future skill prices, θ_0, θ_1, can be allowed to differ across individuals. Individuals' perceptions about their own skills enter via f_i.

Thus in my model I can allow for self-selection into schooling on unobservables, which arises from the anticipated part of the earnings, $\theta_j' f_i$, while the unanticipated ϵ_{ia}^j can obviously not be acted upon.[8] In the 'conventional' Generalized Roy model there is self-selection on U_0 and U_1 (see

[7] Kaufmann and Pistaferri (2009) address the issue of superior information of the individual compared to the researcher in the context of intertemporal consumption choices. They analyze the empirical puzzle of excess smoothness of consumption, i.e. the fact that people respond less to permanent shocks than predicted by the permanent income hypothesis. Data on people's subjective expectations of earnings allow them to disentangle two competing explanations, insurance of even very persistent shocks versus superior information of the individual compared to the researcher. They show that people respond less to permanent shocks than predicted because they anticipate part of what the researcher labels as "shocks", while the role of insurance of very persistent shocks is only minor.

[8] Compare Cunha, Heckman, and Navarro (2005) who analyze which part of idiosyncratic returns is anticipated.

equation (2)) and no distinction between anticipated and unanticipated idiosyncratic returns. For example, 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. Subjective expectations allow me to take into account the part of the idiosyncratic returns that is anticipated and (potentially) acted upon at the time of the schooling decision.

The individual ex-post (gross) return to college in this framework can be written as:

$$\begin{aligned} \widetilde{\rho}_{ia} &= \ln Y_{ia}^1 - \ln Y_{ia}^0 \\ &= \alpha + (\beta_1 - \beta_0)' X_i + \gamma_1 p_{ia}^{W1}(a-22) - \gamma_0 p_{ia}^{W0}(a-18) + (\theta_1 - \theta_0)' f_i + (\epsilon_{ia}^1 - \epsilon_{ia}^0), \end{aligned}$$

where $\alpha = (\alpha_1 - \alpha_0)$. The individual's ex-post return can obviously never be observed, as only one of the two potential outcomes is observable.

Using the information given in equation (3), I can derive an expression for the expected, i.e. ex-ante anticipated, gross return of individual i, which I can observe for each individual given my subjective expectation data:

$$\begin{aligned} \rho_{ia} &= E_{18}(\ln Y_{ia}^1 - \ln Y_{ia}^0) \\ &= \alpha + (\beta_1 - \beta_0)' X_i + \gamma_1 p_{ia}^{W1}(a-22) - \gamma_0 p_{ia}^{W0}(a-18) + (\theta_1 - \theta_0)' f_i. \end{aligned} \tag{4}$$

According to my model of college attendance (see equation (1)), we would ideally want data on expected future earnings over the whole life-cycle of each individual. Unfortunately, I only have data on expected earnings for age 25 (see Section 3). Thus I need to make an assumption about how earnings (expectations) evolve over the life-cycle.

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

Assumption 1 *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 until retirement, that is each year labor market experience increases by p_i^{W0} with a high school degree and with p_i^{W1} with a college degree.*

The assumption of log earnings being additively separable in education and experience is commonly used in the literature (compare, e.g., Mincer (1974)). I assume a deterministic relationship for experience, but instead of using potential labor market experience as a proxy for actual experience as in a Mincer earnings regression, I allow the increase in experience to differ across people depending on their perceived probability of being employed with a high school and college degree (p_i^{W0} and p_i^{W1}), which should capture the fraction of the year that they expect to be employed (see equation (2)). In principle, one would like to use the perceived probability of working for each year over the whole life-cycle, i.e. p_{ia}^{W0} and p_{ia}^{W1} for all $a = 18, ..., A$, but in my data questions on

Subjective expectations incorporate this information directly, as they only include the part that is anticipated.

subjective expectations were only asked for age 25. Therefore I assume $p_{ia}^{Wj} = p_{i25}^{Wj} = p_i^{Wj}$ for all a and for $j = 0, 1$. 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 the college attendance decision– with zero experience.

Assumption 2 *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 Section 4) –that is excess responsiveness of credit-constrained individuals with respect to changes in direct costs– is robust with respect to this assumption: It can also be derived, for example, from the model of Cameron and Taber (2004), who use a similar framework, but assume that constrained individuals face higher borrowing rates than unconstrained individuals during school, while both groups face the same (lower) borrowing rate once they graduate.

Assumption 3 *Individuals are risk-neutral.*

In a framework with uncertainty this assumption implies that the decision problem of college attendance simplifies to maximizing the expected present value of earnings net of direct costs. As I will show in Section 4, perceived earnings and unemployment risk are not significant in a regression of college attendance choice (while they are for the decision to attend high school, see Attanasio and Kaufmann (2009)). For this reason and because taking into account risk would significantly complicate the model, I do not take into account risk considerations here.

Assumption 4 *Individuals have a common discount factor.*

The literature on credit constraints has to deal with three partially unobserved determinants of schooling decisions that are hard to disentangle: expected returns (capturing unobserved skills and information about skill prices), credit constraints (heterogeneity in borrowing rates) and heterogeneity in preferences (e.g. discount rate). Data on subjective expectations help to address part of the identification problem, that is to distinguish between low expected returns of the poor versus high (unobserved) costs, while the problem of disentangling heterogeneity in interest rate and time preferences remains. For example Cameron and Taber (2004) assume a common discount factor for all individuals. One way to address this additional identification problem could be to add survey questions not only on expectations but also on people's time preferences. 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 *The problem is infinite horizon.*

To estimate the model of college attendance choice (see equation (1)), I make use of the data on subjective earnings expectation applying the following approximation $E(Y_{ia}) \equiv E(e^{\ln Y_{ia}}) \cong e^{E(\ln Y_{ia})+0.5Var(\ln Y_{ia})}$. Given the assumptions about returns to experience, I can rewrite the participation equation (1) in terms of expected gross returns to college ρ_i (see Appendix B for the derivation):

$$\begin{aligned} S_i^* &= f\left(r_i, \rho_i, C_i, E_{18}(\ln Y_{i25}^0), p_i^C, p_i^{W1}, p_i^{W0}, \sigma_i^0, \sigma_i^1\right) \\ S_i &= 1 \;\text{ if }\; S_i^* \geq 0 \\ S_i &= 0 \;\text{ otherwise,} \end{aligned} \tag{5}$$

where S_i is a binary variable indicating the treatment status. The decision to attend college depends upon the (unobserved) interest rate r_i, expected return ρ_i, direct costs of attendance C_i, opportunity costs $E(\ln Y_{i25}^0)$, the probability of being employed with college and high school degree, p_i^{W1} and p_i^{W0}, the probability of completing college p_i^C and the (subjective) standard deviations of future earnings σ_i^0, σ_i^1.

Before deriving and testing implications of this model to analyze the role of credit constraints in college attendance decisions, I describe the data that I will be using.

3 Data Description

In this section I describe the data and discuss in detail the module eliciting subjective expectations of earnings and several validity checks of these data.

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 (compare Attanasio and Kaufmann (2009)). The sample was collected to evaluate the program "Jovenes con Oportunidades", which was introduced in 2002/03 and which gives cash incentives to individuals to attend high school and get a high school degree.

Primary sampling units are individuals, who are eligible for this program. There are three eligibility criteria: being in the last year of junior high school (9th grade) or attending high school (10 to 12th grade), being younger than 22 years of age, and being from a family that receives

Oportunidades transfers.[9] As I analyze the college attendance decision in this paper, 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 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 including remittances to and from the household. The youth questionnaire contains a section on individuals' subjective expectations of earnings as discussed in the next section.

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. In principle I would want to have data on people's expectations at the time when they are deciding about attending college, that is some time before college starts in August or September 2005. Instead 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 these two or three months or have changed, but left expectations about future earnings at age 25 –thus seven years later– unchanged. As I do not observe expectations of high school graduates in July or August *before* college starts, I perform the following consistency check of this assumption: I use the cross-section of earnings expectations of a cohort that is one year younger (just starting grade 12) and compare it to the cross-section of expectations of my sample of high school graduates. The distributions of expected earnings (for high school and college as highest degree) do not differ significantly between the two cohorts, suggesting that expectations have not changed significantly in these three months (see Figures 1 and 2). These results can also address the following potential concern: individuals might 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 (or lower expected high school earnings), and those, who decided not to attend, state lower expected college and higher high school earnings. This would lead to a more dispersed cross-section of earnings after the decision (unless people switch positions in the distribution in such a way that the resulting cross-section looks exactly the same as before, that is people with low expected college earnings decide to attend and now state high college earnings and vice versa). I do not find this in my data, which thus provides supportive evidence of my assumption.

[9]Due to the last eligibility criteria the sample only comprises the poorest third of the high school graduate population. Thus even the individuals that I denote as "high" income individuals are not rich. 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.

3.2 The Subjective Distribution of Future Earnings

The subjective expectations module 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?*

   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.

In the following paragraph I briefly describe how the answers to the three survey questions (2(a)-(c)) are used to compute moments of the individual earnings distributions and expected gross returns to college (compare Guiso, Jappelli, and Pistaferri (2002) and Attanasio and Kaufmann (2009)). 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 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. 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.[10]

[10] The first moment of the individual distribution is extremely robust with respect to the underlying distributional assumption (see Attanasio and Kaufmann (2009) for more details on the triangular distribution, alternative distributional assumptions and robustness checks).

Thus I can express expected earnings $E(Y^S)$ and perceived earnings risk $Var(Y^S)$ for schooling degrees $S = 0, 1$ for *each* individual as follows:

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

I will perform the following analysis in terms of log earnings, so that I compute, for example, expected log earnings as $E(\ln(Y^S)) = \int_{y^S_{min}}^{y^S_{max}} \ln(y) f_{Y^S}(y) dy$ and I can thus calculate expected (gross) returns to college as:

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

3.3 Validity Checks of the Data on Expected Earnings and Returns to College

In this section I discuss some descriptive evidence of the validity of the data on subjective expectations of future earnings and returns (for summary statistics see Table 1). The validity of these data is analyzed in more depth in Attanasio and Kaufmann (2009), who conclude that –on average– people have a good understanding of the questions on subjective expectations. In particular their findings suggest that people have decent knowledge about skill prices and about local earnings for different schooling degrees.[11] Investigating how well people are informed has important policy implications, because one explanation for low enrollment rates among the poor could be lack of information (for example about skill prices) leading to an underestimate of returns to schooling or an overestimate of earnings risk. At the same time this question is extremely difficult to answer, as individual returns are never observed –not even ex-post– due to unobserved counterfactual earnings and because the individual is most likely better informed about his own skills and chooses based upon this knowledge, which is not observed by the researcher.

Whether data on subjective expectations can improve our understanding of people's schooling decisions depends crucially on whether these data are able to capture the beliefs that people base their decisions on. Attanasio and Kaufmann (2009) find that subjective expectations are at least a noisy measure of the relevant beliefs and that these data can thus provide a valuable tool in the analysis of school choices. In the following I will discuss a few of these results.

[11] Delavande, Giné, and McKenzie (2009) survey the literature that uses subjective expectations in developing countries and find that in many studies the surveyed individuals were willing to answer the expectations questions and understood them reasonably well –for example with visual helps. They conclude that data on people's subjective expectations can be a useful tool for understanding people's behavior also in the context of developing countries. One advantage of the Mexican survey used here in this paper is the education level of the people interviewed: I use data on subjective expectations of adolescents with a high school degree, who are thus much more likely to understand the probabilistic questions than individuals with lower education levels as in most other studies in developing countries. Studies differ in their findings about how well informed their subjects are. For example, Jensen (forthcoming) finds that eights graders in the Dominican Republic significantly underestimate returns to schooling, while the earnings expectations of the Mexican high school graduates are close to observed earnings, see below.

Attanasio and Kaufmann (2009) compare the level of earnings expectations of Mexican high school graduates to the level of contemporaneous earnings realizations using Census data of the year 2000. This is informative, but not a test of whether people have "correct" expectations, because the expectations are about future earnings which will only be realized in the year 2012. Expected monthly high school earnings are 1940 pesos (and thus approximately 200 US$) compared to mean observed high school earnings of 1880 pesos. Expected college earnings are larger than college earnings observed in the year 2000 (3800 versus 3300 pesos). These results are consistent with people expecting a continuation of previous trends, that is stagnating high school earnings and increasing college earnings. The implied returns –defined as the difference between log college earnings and log high school earnings– are thus around 0.65 and very similar to other studies on Mexico (see, e.g. Binelli (2008) who finds a difference of 0.64 in log hourly wages between higher and intermediate education in 2002 using ENIGH data and compare Carneiro, Heckman, and Vytlacil (2005) who find a log difference of 0.4 for the US).

Attanasio and Kaufmann (2009) show that earnings expectations vary with individual and family background characteristics in a similar way like observed earnings in Mincer earnings regressions. Even after controlling for these characteristics, expectations are strongly correlated with local average earnings for the relevant schooling level and gender (again using Census 2000 data).

These results suggest that people understand the questions on subjective expectations well and are –at least on average– relatively well informed about skill prices and about how individual characteristics affect earnings.

At the same time there is still a considerable amount of heterogeneity in expected earnings, which could reflect measurement error in subjective expectations or could be due to superior information of the individual compared to the researcher, for example about her skills (compare Kaufmann and Pistaferri (2009) for evidence on superior information of people in the labor force about future income, which helps to explain the puzzle of excess smoothness of consumption).

The following result suggests that at least part of the unexplained heterogeneity of subjective expectations is driven by heterogeneity in information sets, such as information about skill prices: People's expectations remain an important determinant of schooling decisions even after controlling for an extensive set of individual and family background characteristics, which reflect the information set of the researcher. This finding points to an important value-added of data on subjective expectations, as these data seem to capture the beliefs that people base their decisions on and help to bridge the differences in information sets between researcher and individual.

Attanasio and Kaufmann (2009) also address the question whose expectations are relevant for the schooling decision, the ones of the adolescent or the ones of the parents. They find that for the high school attendance decision, mothers' as well as adolescents' expectations appear important, while for the college attendance decision only the adolescents' expectations matter. Furthermore, they find that for the high school decision, risk perceptions (about unemployment and earnings risk) matter. For the college attendance decision on the other hand only expectations about returns to college are significant. For this reason I abstract in my model from risk considerations (see Section 2) and focus on adolescents' expected returns and the perceived probability of work (which affects life-time earnings and growth in labor market experience) in the following analysis.[12]

Unfortunately, the survey was not randomized upon who answered the questions on the subjective distribution of earnings (while questions on point expectations were asked to the mothers of every adolescent in the sample): In cases where the adolescent was not present mothers answered also the youth questionnaire –including the questions on the subjective distribution of earnings (see Appendix C for further details and summary statistics in Table 9). I use only the subsample for which the adolescents answer themselves and address the concern of sample selection bias as follows: I 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 Table 10 in Appendix C). Results suggest that sample selection on unobservables is not an important problem, as I find that the correlation between the error terms of the two equations is never significantly different from zero (see Tables 2 to 6). The results are qualitatively the same when using the full sample, i.e. including the adolescents for whom the mothers answer (results from the author upon request).

3.4 Data on Educational Costs

According to the model of college attendance choice (see Section 2) direct costs of attending college should be an important determinant of college attendance decisions in addition to expected earnings. In Mexico these costs pocket a large fraction of parental income for relatively poor families, as will be shown below. Thus they might play an important role in explaining low college attendance rates of the poor.

I collected data on the two most important cost factors, enrollment and tuition costs and costs of living. As costs of living during college depend heavily on the accessibility of universities, I use distance to college as a proxy (compare, e.g., Card (1995) and Cameron and Taber (2004)). For example, if an adolescent lives far away from the closest university, she will have to move to a different city and pay room and board. She thus has to incur important additional costs compared to someone who can live with his family during college. I collected information on the location of higher education institutions offering four-year undergraduate degrees and computed the actual distance between these institutions and the adolescent's locality of residence.[13] About half of the

[12]Given that perceived risk measures are significant in the analysis of high school decisions it appears less likely that their insignificance in college decisions is driven by the measures being too noisy. At the same time I cannot account for differences in risk aversion in this analysis and thus the question about risk perceptions playing a role in higher education decisions requires further research.

[13]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

adolescents live within a distance of 20 kilometers to the closest university, which might permit a daily commute with public transportation. Twenty-five percent live within 20 to 40 kilometers distance, while the other quarter lives more than 40 kilometers away (see summary statistics in Table 1).

In terms of (yearly) tuition and enrollment fees I use administrative data from the National Association of Universities and Institutes of Higher Education (ANUIES). I determine the locality with universities that is closest to the adolescent's locality of residence and use the lowest tuition fee of all the universities in this locality as my cost measure. Fifty percent of adolescents face tuition costs of at least 750 pesos (see Table 1).[14] This is equivalent to 15% of median per capita parental income, while it only represents a fraction of total college attendance costs. Thus college attendance would imply a substantial financial burden for poor families.

To address the question if the ability to finance college costs plays a major role in explaining the income gradient in college attendance, I need proxies for unobserved financing costs (reflected by the interest rate in my model, see Section 2). Financing costs depend mainly on parental income and wealth, which determine the availability of resources, the ability to collateralize and receive loans, and at what interest rate to receive loans or forego savings. It is important to point out that fellowships and student loans play a very limited role for higher education in Mexico: only 5% of the undergraduate student population received a fellowship in 2004, while about 2% benefited from a student loan (for further details on the system of higher education in Mexico, see Appendix C).

The survey provides detailed information on income of each household member, savings if existent, durables and remittances. I create the following two measures: per capita parental income and an index of parental income and wealth.[15] Median yearly per capita income is 5200 pesos (approximately 520 US$). As I do not expect a linear effect of income and wealth on the interest rate that families face, I use the following per capita parental income thresholds: twice the minimum monthly salary (59% of the sample fall into this first category of income below 5,000 pesos) and four times the minimum monthly salary (24% have per capita income between 5,000 and 10,000 pesos, as shown in Table 1), while I use quartiles of the index of parental income and wealth.

Before moving to the next section, it is important to briefly discuss the implications of quality differences of universities for my analysis. In Mexico, like in other countries, universities vary in their quality. The distinction between private and public is not a clear quality indicator: Mexico has public universities with high reputation such as UNAM, top private universities such as ITAM,

Superior). 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 my sample and in all neighboring states– from a web page provided by INEGI (National Institute of Statistics, Geography and Information). My special thanks to Shaun McRae who helped extracting these data.

[14]Unfortunately, the measure of tuition costs is missing for nearly a third of the sample. I include these missings in the excluded category of the dummy of tuition costs to avoid small sample sizes.

[15]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. The index of parental income and wealth is created by a principle component analysis of per capita income, value of durable goods and savings. Only a very selective and richer group of households saves or borrows: 4% of households have savings, while 5% borrow.

but also lower quality private and public universities. Unfortunately I do not know which quality people had in mind when answering the expectation questions. In the following I will argue why this implies that my estimates are lower bounds for the importance of credit constraints. In my analysis credit constraints are identified off people who are poor and have high expected returns but do not attend college. Concerning the expectations these individuals state we can think of the following two cases in which a poor person decides not to attend college. In the first case a poor individual might think that high-quality universities are more expensive and unaffordable for her and she might thus mention expected returns that would result from a lower quality (but more affordable) university. She might consider these returns to be low, in which case she would qualify as "not constrained" in my analysis, while she might have been constrained to go to the high-quality university. In the second case the poor individual might have thought of a high-quality university when answering the questions on expected returns and stated high expected returns (while she might have considered low-quality universities to give low returns). In this case she is correctly identified as credit constrained.

In the next section, I derive testable implications of the model of college attendance in the presence of credit constraints and present the empirical results.

4 Testable Implications of the Model of College Attendance Choice and Empirical Results

In the Mexican context parental income and wealth remain an important determinant of college attendance choices, even after controlling for people's beliefs about returns to schooling (see Table 2). Thus with data on subjective expectations I can exclude the possibility that parental income is significant, *only* because it picks up differences in earnings expectations and perceived risk between poor and rich individuals (due either to ability differences or to differences in information sets). These data allow me to control for a determinant that has been neglected in the literature by bridging differences in information sets between researcher and individual.

For a more rigorous analysis of what is causing the income gradient in college attendance, I test implications of the model of college attendance in the presence of credit constraints, while taking into account people's expectations using subjective expectation data as discussed in Section 2.

4.1 The Distribution of Costs of College Attendance for Rich and Poor Individuals

Data on people's expected returns to college as well as on their attendance decision permit to directly estimate the distribution of college attendance costs. These data thus solve the fundamental identification problem that Manski (2004) pointed out. I can evaluate if poorer individuals face higher costs of attending college than rich individuals or if –on the other hand– the lower attendance of the poor is entirely driven by lower expected returns. The latter could be due to differences in "college preparedness" (see, e.g., Carneiro and Heckman (2002)) or to differences in information sets, for example in terms of which factors influence earnings or simply in terms of information about skill prices.

To illustrate how data on expected returns allow to estimate the distribution of costs, consider the stylized model of schooling investments by Becker (1967). In this model direct schooling costs are zero and credit constraints are modeled as heterogeneity in individuals' interest rates. People decide to attend college if expected returns are larger than the interest rate they face:

$$S = 1 \Leftrightarrow \rho \geq r.$$

Thus with data on schooling decisions ($S = 0, 1$), and on expected returns ρ, and the assumption that ρ and r are orthogonal, it is possible to derive the cumulative distribution function of the interest rate r:[16]

$$Pr(S = 1|\rho = \tilde{\rho}) = Pr(r \leq \tilde{\rho}|\rho = \tilde{\rho}) = F_{r|\rho=\tilde{\rho}}(\tilde{\rho}) = F_r(\tilde{\rho}). \tag{6}$$

Intuitively, the fraction of people who decide to attend college given that they expect return $\tilde{\rho}$ is equivalent to the fraction of people who face an interest rate r smaller than expected return $\tilde{\rho}$.

In the absence of credit constraints every individual faces the same interest rate r_0. The implied distribution function of interest rates is a step function, as every individual with expected returns below interest rate r_0 decides not to attend college, while every individual with expected returns above this interest rate decides to attend. My empirical results suggest instead a large degree of heterogeneity in the interest rate r. In that case I should find that poor individuals face a higher interest rate, due for example to lack of collateral. To test this hypothesis I estimate the interest rate distribution separately for different income categories.

In the case of my more general model (see Section 2), which allows for nonzero direct costs of attendance, I show that it is possible to write the participation equation approximately as additively separable between expected return ρ and total college attendance costs K, including direct costs and financing costs (for the derivation see Appendix B).[17] Then total costs K take the place of the interest rate r in the equations of this section, and I can perform the analysis estimating the distribution of total costs.

I estimate the cost distribution $F_r(\tilde{\rho}) = Pr(S = 1|\rho = \tilde{\rho})$ by performing Fan's (1992) locally weighted linear regression of college attendance S on the expected return ρ.[18] To compare the

[16] The orthogonality assumption has the following caveat: It will be violated in a framework with search costs if people with higher expected returns exert more effort into the search for a lower interest rate.

[17] 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,... (see Appendix B).

[18] I use a Gaussian kernel and a bandwidth of 0.3. A smaller bandwidth will lead to a more wiggly line, while the result of a significant right shift in the c.d.f. of costs for poorer individuals remains unchanged. Note that the c.d.f.

distribution function for different income classes, I perform this analysis for "low", "middle" and "high" income individuals, i.e. yearly per capita income less than 5,000 pesos, between 5,000 and 10,000 pesos and more than 10,000 pesos, where the thresholds correspond to twice and four times the minimum wage (see data section 3.4). I calculate point-wise confidence intervals applying a bootstrap procedure.

Figure 4 shows that that poor individuals face higher costs than the rich, as the c.d.f. of costs is shifted to the right for poorer individuals. Take for example an interest rate of $r = 0.6$ (which is equal to the median gross return defined as the difference between expected log college and high school earnings, see Section 3.3). More than 75% of the poor face an interest rate higher than $r = 0.6$, while only 55% of the rich individuals face costs $r > 0.6$. To put it differently, among individuals with expected returns around $\rho = 0.6$, 45% of rich individuals attend, but only 25% of the poor. Poor individuals thus require higher expected returns to be induced to attend college. These differences are significant, as Figure 5 illustrates, which plots the c.d.f. of poor and rich individuals with 95%-confidence intervals.

4.2 Excess Responsiveness of the Poor to Changes in Direct Costs

In the last section I have shown that 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 different cost components and whether credit constraints play an important role in the low enrollment rate of poor Mexicans, I derive the following testable prediction of the presence of credit constraints from my model of college attendance choice. As discussed in Section 2, credit constraints are captured by heterogeneity in the interest rate that people face.

My model of college attendance choice implies that individuals who face a high interest rate r react more strongly to changes in direct costs C (see equation (19) in Appendix B):

$$\left| \frac{\partial S^*}{\partial C} \right| \quad \text{is increasing in} \quad r. \tag{7}$$

Intuitively, an increase in costs has to be financed through a loan (or foregone savings) with interest rate r. The negative impact of a cost increase is thus larger for people who face a large interest rate.

I test this prediction using dummies for groups that are likely to face different interest rates if credit constraints are important, that is I use dummies 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 credit constrained groups to changes in direct costs is not specific to my model. This prediction can be derived from a more general class of school

of costs can only be estimated over the support of the expected return (see equation (6)).

choice models, such as for example from the model of Cameron and Taber (2004). They have more general assumptions concerning heterogeneity in interest rate (see Section 2), i.e. they allow for r to be different between credit constrained and unconstrained individuals during school while r is the same for both groups after school. Cameron and Taber (2004), Card (1995) and Kling (2001) 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, data on subjective expectations provide the following two advantages: First, I can control directly for people's expectations about their potential returns to college and thereby avoid biased estimates that could arise from omitting this determinant. This makes my test more robust and enables me to analyze the validity of the test used without controlling for people's expectations. 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, as they are the ones likely to be close to the margin of indifference ($S^* = 0$). Poor low-return individuals on the other hand would not 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.

The first cost measure that I use is distance of the adolescent's home to the closest university (see data section 3.4). As shown in Table 2 living further away from the closest university has a significantly negative effect on the probability to attend college. Table 3 illustrates that the negative effect of a larger distance is particularly strong for poor individuals as predicted by the model in the presence of credit constraints. Living 20 to 40 kilometers away from college instead of less than 20 kilometers decreases the probability of attending by about 9 percentage points for the poorest income category and this negative effect is significantly larger for the poor than for the rich (p-value 0.07). Increasing the distance to more than 40 kilometers has a large effect for the middle income category, but the coefficients for the different income categories are not significantly different from each other. A comparison between the first and second column of Table 3 shows that including measures of expectations does not change the results.

The conclusions remain unchanged when I use a different proxy for being credit constrained, that is quartiles of an indicator of parental income and wealth (for the exact definition of the two income (and wealth) measures, see data section 3.4). Table 4 shows that an increase of the distance to more than 20 kilometers has the largest impact for the poorest parental income and wealth quartile. It decreases the likelihood of attending college by about 12 percentage points and this effect is significantly stronger for the poorest than for the richest quartile (p-value 0.02).[20]

[19] Card (1995) and Kling (2001) find evidence of important credit constraints for an older cohort of the National Longitudinal Survey (NLS Young Men), while Cameron and Taber (2004) do not find evidence of credit constraints for the U.S.A. using the NLSY 1979. This is consistent with increased availability of fellowships and loans in the U.S.A. over the relevant time period.

[20] These results are not driven by how the poor and the rich compare in terms of distance: The fraction of people living between 20 and 40 kilometers (or more than 40 kilometers) from the closest university is very similar for all four income/wealth quartiles, while in terms of the three income categories the poor are slightly more likely to live

Increasing the distance to more than 40 kilometers has a large negative effect for the third quartile, but the coefficients for the different income categories are not significantly different from each other. It is important to keep in mind that in this analysis credit constraints are identified by comparing the poorest individuals to the richer individuals in my sample, who are themselves relatively poor. Thus it is likely that my results underestimate the importance of credit constraints.

In terms of the second cost measure I use yearly tuition and enrollment fees. In particular I use a dummy for tuition costs above 750 pesos (the median), which is equivalent to 15% of median yearly per capita income and thus represents an important financial burden for poor individuals. The first two columns of Table 5 would suggest that tuition costs do not have any effect on attendance. But once we take into account that what matters is being poor *and* having high expected returns, results change: Poor individuals with high expected returns are excess responsive with respect to a change in tuition costs. An increase in tuition to more than 750 pesos reduced the likelihood to attend by 12 percentage points for poor high-return individuals. The negative effect of an increase in costs is significantly larger for the poor than for the rich (p-value 0.09). The same picture arises using quartiles of the parental income and wealth indicator (see Table 6). For individuals in the lowest income/wealth quartile with high expected returns an increase in tuition costs reduces their likelihood to attend by about 15 percentage points (significantly larger in absolute value than for the top quartile, with a p-value of 0.08). [21]

Thus results of this section are consistent with the predictions of a model with credit constraints.

5 Counterfactual Policy Experiments

In the previous section I have shown that poor people face significantly higher costs of college attendance than rich people and that poor high-expected-return individuals are most sensitive to changes in direct costs. These results suggest that credit constraints affect college attendance decisions of poor Mexicans with high expected returns. Nevertheless I cannot exclude the possibility that other factors are also driving the low college attendance rates among poor.[22] Even if the empirical fact mostly reflects heterogeneity in time preferences, for example, government policies such as student loan programs might still be recommendable. This would 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.

As credit constraints would create scope for policy interventions, I perform counterfactual policy

further away. Note that what I call "rich" are still relatively poor people below the median income in society.

[21] In the previous tables I do not include distance interactions and tuition interactions jointly. Including them jointly does not change the conclusions about comparing coefficients between poor and rich.

[22] As discussed, data on subjective expectations help to address part of the identification problem that the literature on credit constraints faces, that is to distinguish between low expected returns of the poor versus high (unobserved) costs, while the problem of disentangling heterogeneity in interest rate and time preferences remains. One way to address this additional identification problem could be to add survey questions not only on expectations but also on people's time preferences.

experiments by applying the Local Instrumental Variables methodology of Heckman and Vytlacil (2005) to my model of college attendance making use of data on subjective expectations of earnings. In particular I evaluate potential welfare implications of the introduction of a fellowship program that can be means-tested and performance-based. I estimate the fraction of people changing their decisions in response to a reduction in direct costs, and derive the expected returns of those individuals ("marginal" expected returns).

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 be facing particularly high unobserved costs, as they would otherwise also be attending college given their high expected returns.

One word of caution is necessary before describing the counterfactual policy experiments. As argued in this paper, data on people's subjective expectations can be very useful for understanding people's behavior, as the data seems to be able to measure the beliefs that people base their actions on (compare Section 3.3). For the welfare analysis on the other hand one would like to know people's actual returns, which are never observed. Given that people seem to have a good understanding of their potential earnings (see Section 3.3) and most likely have a better knowledge of their own skills, people's expectations might be relatively realistic. Nevertheless it is very hard to evaluate the rationality of expectations and thus the policy-experiments should be taken with caution in terms of quantitative evaluation of the welfare benefits and seen more as an additional piece of evidence concerning the importance of borrowing constraints, as explained below.

The idea of the third test of credit constraints comparing marginal returns to returns of those attending school is directly linked to Card's interpretation of the finding that in many studies instrumental variable (IV) estimates of the return to schooling exceed ordinary least squares (OLS) estimates (Card (2001)). 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 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 two problems in terms of how the idea was implemented (compare Carneiro and Heckman (2002)) and one more fundamental problem in terms of assumptions about people's information sets. I will argue how these problems can be addressed using data on subjective expectations. In terms of the implementation, the validity of many of the instruments used in this literature has been questioned, thus challenging the IV results.[23] Second, even granting the validity

[23] 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.

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 who attend 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 $E(\beta|S=1)$.[24]

Data on subjective expectations allow me to directly test the validity of the instrument that I will be using to compute marginal returns and perform policy experiments: In contrast to the situation with earnings realizations, subjective expectations are asked for both possible states of highest potential schooling degree, i.e. I also have data on "counterfactual earnings". Therefore I can compute expected returns for each individual and test if returns are orthogonal to distance to college, which is the instrument that I will be using. With data on each individual's expected return I can also directly address the second problem of implementation: I can directly compute the average (expected) return of the adolescents who attend college and I do not have to rely on OLS. Therefore I can compare marginal returns with returns of the individuals who chose to attend in the spirit of Card's idea.

Even if this test could be implemented with data on earnings realizations alone, the following fundamental problem concerning people's information sets would remain: People at the margin might have –ex-post– higher returns than those who attend. But these people might have decided not to attend because they expected low returns *ex-ante*. As argued before data on people's subjective expectations permit to relax the rational expectations assumption with strong requirements on coinciding information sets of individuals and the researcher.

To test the validity of the instrument used here, I regress expected returns on polynomials of distance to college and tuition costs in the first column (in addition to observable characteristics of the individual and her family background, such as GPA of junior high school, parents' education, per capita parental income) and on the dummies I use for distance and tuition costs in the second column. Table 11 (see Appendix C) shows that neither the coefficients on distance to college nor on tuition costs are significantly different from zero. The table presents results for distance and squared distance, but adding further polynomials does not change the result.

5.1 Implications of Credit Constraints for Marginal Returns to College

From the latent index model (see equation (5)), I can derive the return at which an individual is exactly indifferent between attending college or not, in which case $S^* = 0$:

[24] $E(\ln Y_1|S=1) - E(\ln Y_0|S=0) = E(\beta|S=1) + (E(\ln Y_0|S=1) - E(\ln Y_0|S=0))$, 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.

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

$$S_i^* = f\left(r_i, \rho_i^M, C_i, E(\ln Y_{i25}^0), p_i^C, p_i^{W1}, p_i^{W0}, \sigma_i^0, \sigma_i^1\right) = 0 \tag{8}$$

The presence of credit constraints has the following implication for marginal returns: implicit differentiation of equation (8) 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 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.

5.2 Derivation of the Marginal Return to College

For the purpose of the third test –comparing the expected returns of people at the margin of attending to those already attending– and to perform counterfactual policy experiments, I illustrate in this section how the "Marginal Treatment Effect" (MTE) can be derived, following Carneiro, Heckman, and Vytlacil (2005) and Heckman and Vytlacil (2005).

One important first step in the derivation and estimation of the marginal return to college is the estimation of the propensity score $P(Z) \equiv P(S = 1|Z = z)$. $P(Z)$ represents the probability of attending college conditional on observables Z. To estimate the participation equation, I perform the following monotonic transformation of $S^* = \nu(Z) - V$:

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

and define $\mu(Z) \equiv F_V(\nu(Z))$ and $U_S \equiv F_V(V)$. In this case U_S is distributed uniformly, $U_S \sim$ Unif$[0,1]$.[25] 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, i.e. the (marginal) costs which are equal to r in my

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

model, for the indifferent individual by estimating the propensity score $P(Z)$.

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

$$\Delta^{MTE}(u_S) = E(\ln Y_1 - \ln Y_0 | U_S = u_S) = E(\rho | U_S = u_S). \tag{9}$$

It represents the average gross gain to college for individuals who are indifferent between attending college or not at the level of unobservable costs $U_S = u_S$.

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, Vytlacil, and Urzua (2006)).

In a model with heterogeneity in interest rates, data on subjective expectations allow me to write the participation equation in additively separable form: The participation equation as derived from the model can be expressed as a fourth-order polynomial in the unobservable interest rate, $1 + r$ (see Appendix B for the derivation):

$$S_i^* \geq 0 \Leftrightarrow (1 + r_i)^4 - A(Z_i; \theta)(1 + r_i)^3 - B(Z_i; \theta) \leq 0, \tag{10}$$

where $A(Z_i; \theta), B(Z_i; \theta) > 0$ are functions of $Z_i = \left(\rho_i, C_i, E(\ln Y^0), p_i^{W1}, p_i^{W0}, p_i^C, \sigma_i^0, \sigma_i^1\right)$ 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:

$$\begin{aligned} S_i^* &= -(1 + \bar{r}) + g\left(Z_i; \theta\right) - V_i \\ S_i &= 1 \;\text{ if }\; S_i^* \geq 0 \\ S_i &= 0 \;\text{ otherwise.} \end{aligned} \tag{11}$$

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: 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.

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):

$$\begin{aligned} \int_0^p E\left(lnY_{it}^1 - lnY_{it}^0 | U_S = p\right) dU_S &= pE\left(lnY_{it}^1 - lnY_{it}^0 | U_S \leq p\right) \\ &= pE\left(lnY_{it}^1 - lnY_{it}^0 | P(Z) = p, S = 1\right). \end{aligned} \tag{12}$$

With subjective expectations of earnings one has data on each individual's expectation of earnings in both schooling states, and can thus compute $E\left(lnY_{it}^1 - lnY_{it}^0 | S = 1\right)$. 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 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 $p = u_S$:

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

I calculate standard errors by applying a bootstrap over the whole procedure described in this section (including estimation and prediction of $P(Z)$).

To perform policy experiments, I introduce the following notation (see Heckman and Vytlacil (2001)): 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. One important assumption underlying this analysis is that the participation equation continues to hold under hypothetical interventions. The $PRTE$ can be written as:

$$PRTE = \int_0^1 MTE(u)\omega(u)du, \quad \text{where} \quad \omega(u) = \frac{F_P(u) - F_{P^*}(u)}{E(P^*) - E(P)}. \tag{13}$$

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 unobservable costs, 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 probability of attending, $P(Z^*)$.

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.

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:

$$PRTE_\varepsilon = E(\rho_i | Z'\gamma \leq V \leq Z'\gamma + \varepsilon\gamma_k), \tag{14}$$

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.

5.3 Estimation of the Marginal Return to College

This section describes the estimation of the marginal return to college, and discusses the empirical results of this estimation, while the next section discusses the results of the policy experiments.

First I estimate the propensity score from a reduced-form version of the participation equation (11) using a Maximum Likelihood procedure (compare Carneiro, Heckman, and Vytlacil (2005)). In order to empirically implement the notion of costs, C, I use the following auxiliary regression containing dummies for the distance to the closest university, a dummy for tuition costs above 750 pesos, and state fixed effects to capture differences in direct costs. To proxy for preferences and capture monetized psychological costs and to proxy for the probability of completing college, I include parents' education and past school performance, i.e. GPA of junior high school (compare Stinebrickner and Stinebrickner (2009) who show that updating about ability is important for the drop-out decision, while I use past school performance as a proxy for the perceived probability of completing college at the time of deciding about initial college attendance).

The results of the Maximum Likelihood Estimation of the propensity score are displayed in Tables 3 and 5 and discussed in Section 4.2.[26]

Second, I determine the relevant support for the MTE by estimating the density of the predicted probability of attending college. I compare the density for high school graduates, who decided to attend college ($S = 1$), with the one of those, who stopped school after high school ($S = 0$), using

[26] To be precise the tables present coefficient estimates either using interactions of distance or interactions of tuition as cost variable, while in this section I include both types of interactions jointly. The coefficient estimates are very similar to the ones displayed. In particular the coefficients on the cost-income interactions are significantly larger in absolute value for the poor compared to the rich.

smoothed sample histograms. Figure 6 shows that the probability of attending college is generally relatively low for adolescents of the Jovenes sample, but that there is a right-shift in the density for high school graduates, who decided to attend college. Their mean (median) probability is about 34% (32%), while the mean (median) probability of attending for those who stopped is around 26% (24%). Figure 6 illustrates that there is little mass outside of the interval 0.08 and 0.67. Therefore I estimate the marginal return to college over the support p in the interval $[0.08, 0.67]$.

Third, I estimate the MTE. I estimate 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 $u_s = P(Z)$. Figure 7 displays the marginal return to college for three different bandwidths using a Gaussian kernel. One can see that the choice of bandwidth controls the trade-off between bias and variance: while a relatively small bandwidth of 0.1 leads to a wiggly line that is clearly undersmoothed, a large bandwidth of 0.2 seems to lead to an oversmoothed graph.

Lastly, I calculate standard errors by performing a bootstrap over the whole procedure discussed above. Figure 8 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 $P(Z)$ for which there are few data points.[27]

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

5.4 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 governmental fellowship program or tuition subsidies. Therefore I analyze the effect of a change in direct costs on the likelihood to attend college. To simulate the effect of a means-tested and a merit-based policy, I perform this analysis separately for poor and for poor and able individuals. Means-tested policies are important as resources are limited and should help to target the policy to those individuals most likely to be constrained. Eligibility based on merit –determined for example in terms of previous school performance–, has the advantage that the policy supports individuals who are more likely to actually complete college instead of dropping out.[28]

In this analysis I compute the fraction of people changing their decisions as a result of the policy and derive the average "marginal" expected returns of these individuals. I estimate the "Policy Relevant Treatment Effect" ($PRTE$) for the policies of interest, which will be a weighted

[27] Carneiro, Heckman, and Vytlacil (2005) have the same problem of 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.

[28] My measure of previous school performance, GPA, is of course only a noisy predictor of the likelihood to complete college. Nevertheless, my results show that targeting the policy to the poorest and best performing students would induce individuals with the highest expected returns to attend college, which is reassuring.

average of the marginal returns to college (MTE), as determined in the previous section. For the evaluation of policies it is crucial to derive the "marginal" return instead of the "average" return of a randomly selected individual, because only the people "at the margin" are the ones who will respond to policies.

Second, I test whether the average "marginal" expected return is significantly larger than the average expected return of individuals attending college. Thus with subjective expectations I can improve on the test suggested by Card (2001). Larger "marginal" returns indicate that individuals at the margin face higher unobserved costs.

The first policy I evaluate is a decrease in the distance to the closest university. This could be seen as a literal decrease in the distance by building new universities in places that previously did not have higher education institutions or as a reduction in direct costs via fellowships for costs of living. Of course the implied costs of the two policies are likely to be very different and are very difficult to determine. In addition the analysis in this section does not take into account general equilibrium effects of government policies. Thus the goal of this section is not a complete cost-benefit-analysis, but to test for credit constraints by comparing expected returns of people at the margin to the ones of those already attending and to give an idea of potential welfare benefits of government policies such as fellowship programs in Mexico.

In Section 4.2 I have shown that a change in distance to college affects poor high-return individuals most. In addition I take into account in this section, that a change in costs can only affect individuals at the margin. I perform the analysis by decreasing the distance to college by 20 kilometers (for different target groups). This counterfactual policy leads to an increase in college attendance of about 4% (1 percentage points), and to an average marginal expected return of 0.91 (see Table 7). Decreasing the distance only for very poor individuals (less than 5,000 pesos per capita income), leads to a change in attendance of 2%, while those individuals who change college attendance have an average marginal expected return of 0.92. For very poor and very able individuals (per capita income less than 5,000 pesos and GPA in the top tercile), this policy would lead to a change in attendance of about 1%, and an average marginal expected return of 0.93. The expected returns of this last group (very poor and high-performing) is significantly larger that the average expected return of people already attending (0.71), while one cannot reject that the average expected return of the other two groups at the margin is as high as the return of those already attending. 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 high expected returns.

As a second policy experiment, I consider the effect of a 10% decrease in tuition costs, for example via tuition subsidies. A 10% reduction in tuition costs leads to an average marginal return of 0.83, 0.79 for the poor and 0.81 for the poor and able, which is as high as the average expected return of those individuals attending (see Table 7). Unfortunately, tuition costs are very noisily measured, so standard errors for the fraction of "switchers" and for the marginal returns are large.

Again, for a full cost-and-benefit analysis one would have to take into account the costs of a government policy. 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. It would be an interesting topic for future research to analyze how people update beliefs about future returns to schooling given the introduction of such a policy.

6 Conclusion

The goal of this paper has been to improve our understanding of the huge differences in college enrollment rates between poor and rich students in Mexico and to show how data on people's subjective expectations of earnings can help in this endeavor.

When examining reasons for low school attendance among the poor, researchers face the following identification problem: On the one hand poor people might expect particularly low returns to schooling –due for example to lower cognitive skills or perceptions of limited career opportunities even with a college degree–, and thus decide not to attend. On the other hand they might face high attendance costs that prevent them from attending despite high expected returns.

To address this identification problem, I use data on people's subjective expectations of their idiosyncratic returns to college as well as on their college attendance choice. Since what matters for people's decisions is the perception of their own cognitive and social skills and their beliefs about future skill prices, these data ideally provide people's expectations conditional on their information sets at the time of the decision. These data thus help to relax strong assumptions of conventional approaches about people's information sets and about how they form expectations, which were necessary to address the identification problem in the absence of data on subjective expectations.

My results have shown that poor individuals require significantly higher expected returns to be induced to attend college, implying that they face higher costs than individuals with wealthy parents. I found that poor individuals with high expected returns are particularly responsive to changes in direct costs, which is consistent with the predictions of a model with credit constraints.

Evaluating potential welfare implications by applying the Local Instrumental Variables approach of Heckman and Vytlacil (2005) to my model, I found that a sizeable fraction of poor individuals would change their decision and attend in response to a reduction in direct costs. Individuals at the margin have expected returns that are as high or higher than the ones of individuals already attending college, which is consistent with credit constraints playing an important role.

My results suggest that credit constraints are one of the driving forces of Mexico's large inequalities in access to higher education and low overall enrollment rates and point to large welfare gains of introducing a governmental fellowship program by removing obstacles to human capital accumulation and fostering Mexico's development and growth.

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Appendix A

Figure 1: Comparing Expectations of High School Graduates with a One-Year Younger Cohort

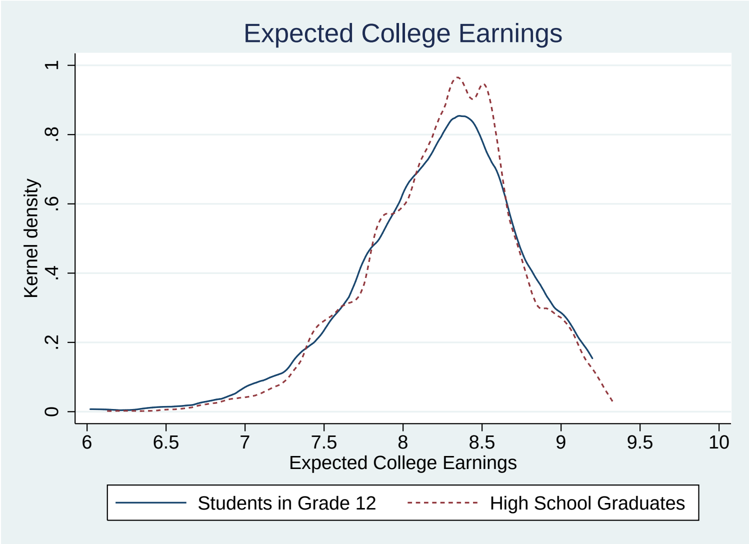

Figure 2: Comparing Expectations of High School Graduates with a One-Year Younger Cohort

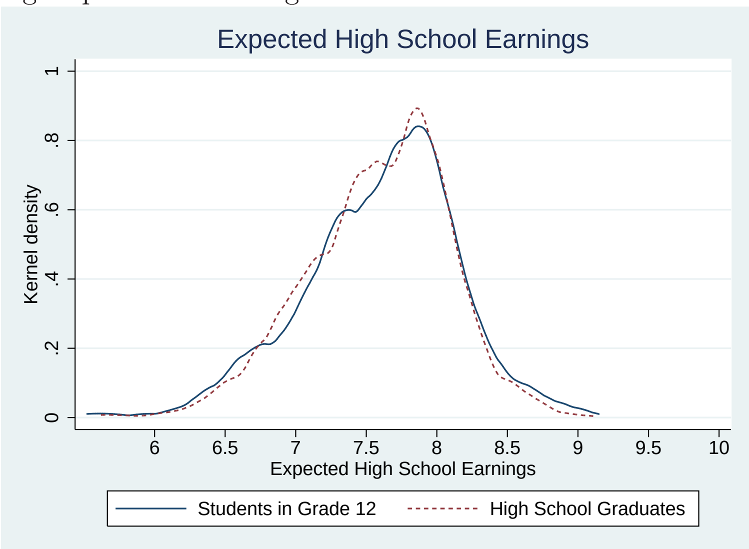

Figure 3: The Triangular Distribution of Earnings

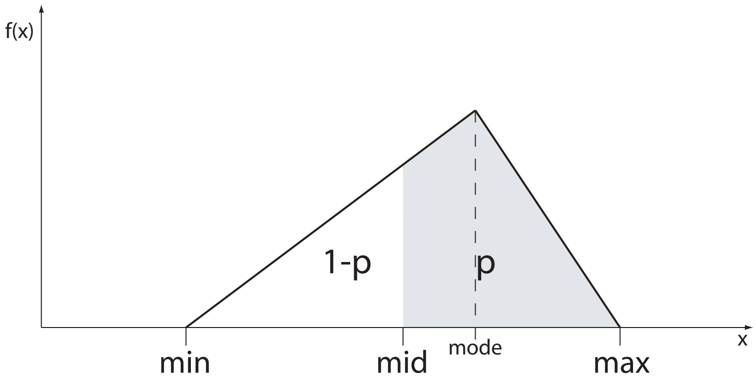

Figure 4: The Cumulative Distribution Function of Costs for Different Income Classes.

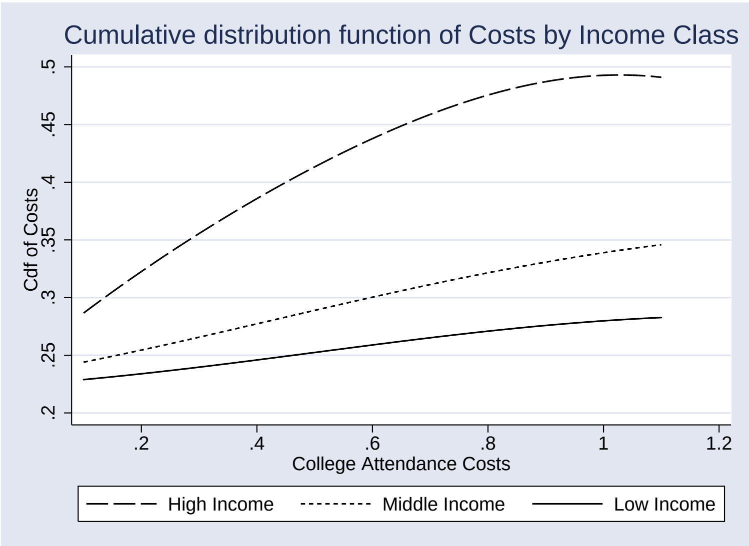

Figure 5: The Cumulative Distribution Function of Costs with 95% Confidence Intervals.

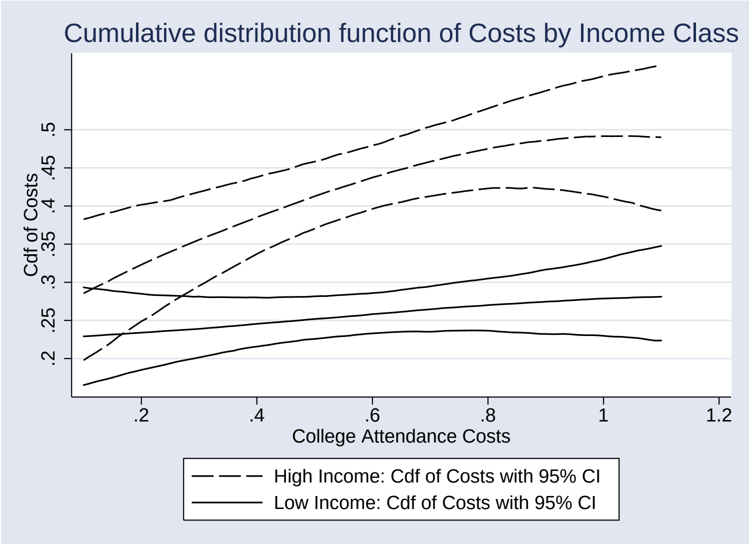

Figure 6: The Predicted Probability of Attending College.

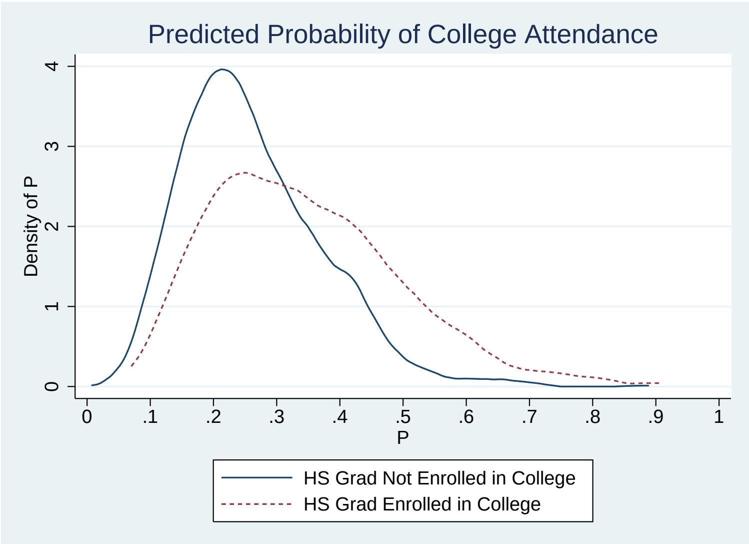

Figure 7: The Marginal Return to College for Different Levels of Unobserved Costs.

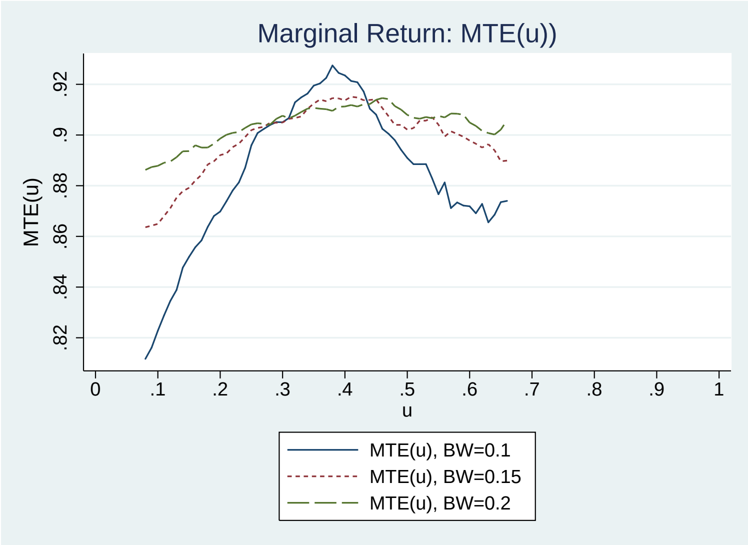

Figure 8: The Marginal Return to College with 95% Confidence Interval Bands.

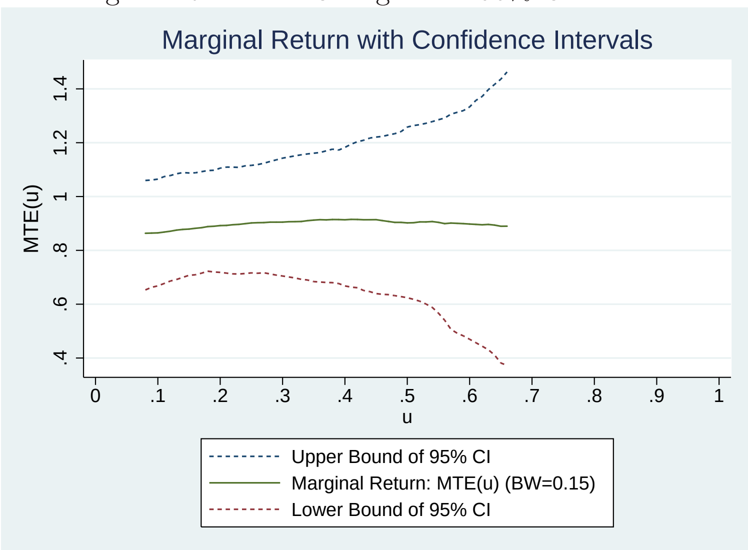

Table 1: Summary Statistics.

Variable	Obs	Mean	Std. Dev.	Median
Expected Return	1612	0.6670	0.3820	0.6047
Expected Log High School Earnings	1612	7.5778	0.5004	7.6432
Var of Log High School Earnings	1612	0.0054	0.0079	0.0028
Var of Log College Earnings	1612	0.0039	0.0061	0.0019
Prob of Work High School	1612	0.6657	0.1817	0.7
Prob of Work College	1612	0.8250	0.1601	0.9
College Attendance Rate	1612	0.2308	0.4215	0
Female	1612	0.5813	0.4935	1
GPA (Scale 0 to 100)	1612	82.19	7.16	82
GPA Second Tercile	1612	0.2804	0.4493	0
GPA Top Tercile	1612	0.2773	0.4478	0
Father's Yrs of Schooling	951	5.33	2.96	6
Father's Educ Jr High School	1612	0.1067	0.3088	0
Sr High School	1612	0.0292	0.1683	0
College	1612	0.0050	0.0703	0
Mother's Yrs of Schooling	1140	5.03	2.77	5
Mother's Educ Jr High School	1612	0.1234	0.3291	0
Sr High School	1612	0.0174	0.1307	0
College	1612	0.0037	0.0609	0
Per Capital Parental Income (Pesos)	1187	7519.54	8010.08	5200
Per Capita Parental Income $<$ 5000 Pesos	1612	0.5906	0.4692	1
5000 to 10000 Pesos	1612	0.2407	0.4276	0
$>$ 10000 Pesos	1612	0.1687	0.3746	0
Distance to University (km)	1612	24.2312	22.8159	18.26
Distance to University $<$ 20 km	1612	0.5298	0.4993	1
20 to 40 km	1612	0.2599	0.4387	0
$>$ 40 km	1612	0.2103	0.4076	0
Tuition Costs (Pesos)	1171	608.8104	634.5729	750
Tuition Costs above 750 Pesos	1612	0.4187	0.4935	0

Table 2: Probit Model of the College Attendance Decision.

Dep. Var.: Attend College	Model 1	Model 2	Model 3
	Marg. Eff./(S.E.)	Marg. Eff./(S.E.)	Marg. Eff./(S.E.)
Expected Return to College	0.092***	0.078**	0.077**
	(0.033)	(0.034)	(0.034)
Prob of Work - Sr HS	0.032	0.013	0.005
	(0.087)	(0.085)	(0.081)
Prob of Work - College	-0.008	-0.001	0.032
	(0.101)	(0.099)	(0.092)
Var of Log Earn - Sr HS	-2.625	-3.016	-2.959
	(1.919)	(2.008)	(1.958)
Var of Log Earn - College	-0.310	0.036	0.196
	(2.351)	(2.291)	(2.164)
Female	-0.055*	-0.059*	-0.046
	(0.029)	(0.033)	(0.032)
GPA - Second Tercile		0.055*	0.055*
		(0.031)	(0.031)
GPA - Top Tercile		0.187***	0.174***
		(0.038)	(0.045)
Father's Educ - Jr HS		0.099**	0.073*
		(0.042)	(0.042)
Father's Educ - Sr HS		0.151*	0.100
		(0.078)	(0.075)
Father's Educ - Univ		0.547***	0.574***
		(0.120)	(0.131)
Mother's Educ - Jr HS		0.100**	0.074*
		(0.040)	(0.039)
Mother's Educ - Sr HS		0.203**	0.173*
		(0.099)	(0.101)
Per Cap Income - 5 to 10k			0.051*
			(0.031)
Per Cap Income - more than 10k			0.119***
			(0.037)
Dist to Univ 20 to 40km			-0.076***
			(0.029)
Dist to Univ above 40km			-0.106***
			(0.031)
Tuition Above 750 Pesos			-0.082**
			(0.039)
State FE	Yes	Yes	Yes
Observations (Censored)	3342 (1730)	3342 (1730)	3342 (1730)
Log Likelihood	-3041.971	-2990.349	-2972.964
Sample Sel.: Corr. betw. Errors (P-Val)	-0.487 (0.055)	-0.282 (0.314)	-0.131 (0.654)

Notes: Table displays marginal effects and standard errors in brackets. * p<0.1 ** p<0.05 *** p<0.01. Excl. categories: male, lowest GPA tercile, father's and mother's education primary or less (mother's education university not displayed, as not significant due to small number of obs), per capita income less than 5000 pesos, distance to university less than 20 km and tuition less than 750 pesos.

Table 3: Excess Responsiveness of the Poor to Changes in Direct Costs (Distance to College).

Dep. Var.: Attend College	Model 4 Marg. Eff./(S.E.)	Model 5 Marg. Eff./(S.E.)	Model 6 Marg. Eff./(S.E.)
Univ 20 - 40km * Par Income $<$ 5k	-0.089**	-0.092**	-0.076
	(0.044)	(0.044)	(0.059)
Univ 20 - 40km * Par Income $<$ 5k * High Exp Ret			-0.067
			(0.083)
Univ 20 - 40km * Par Income 5 - 10k	-0.044	-0.049	-0.041
	(0.054)	(0.054)	(0.078)
Univ 20 - 40km * Par Income 5 - 10k * High Exp Ret			-0.022
			(0.109)
Univ 20 - 40km * Par Income $>$ 10k	0.053	0.048	0.062
	(0.071)	(0.070)	(0.099)
Univ 20 - 40km * Par Income $>$ 10k * High Exp Ret			-0.026
			(0.119)
Univ $>$ 40km * Par Income $<$ 5k	-0.048	-0.051	-0.041
	(0.043)	(0.043)	(0.058)
Univ $>$ 40km * Par Income $<$ 5k * High Exp Ret			-0.064
			(0.081)
Univ $>$ 40km * Par Income 5 - 10k	-0.136***	-0.145***	-0.160**
	(0.051)	(0.050)	(0.069)
Univ $>$ 40km * Par Income 5 - 10k * High Exp Ret			0.046
			(0.152)
Univ $>$ 40km * Par Income $>$ 10k	-0.045	-0.047	-0.152**
	(0.071)	(0.072)	(0.075)
Univ $>$ 40km * Par Income $>$ 10k * High Exp Ret			0.292
			(0.200)
Par Income $<$ 5k * High Exp Ret			0.088
			(0.059)
Par Income 5 - 10k * High Exp Ret			0.184**
			(0.084)
Par Income $>$ 10k * High Exp Ret			0.132
			(0.093)
Controls for Expected Return, Exp Log Earn, Prob of Work and Var of Log Earn	No	Yes	Yes
Controls: GPA, Par Income and Educ, Sex, State FE	Yes	Yes	Yes
Observations (Censored)	3342 (1730)	3342 (1730)	3342 (1730)
Log Likelihood	-2984.591	-2971.787	-2965.898
Sample Sel.: Corr. betw. Errors (P-Val)	-0.167 (0.569)	-0.172 (0.556)	-0.112 (0.709)

Notes: Table displays marginal effects and standard errors in brackets. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Excl. categories: male, lowest GPA tercile, parents' education primary or less, per capita income less than 5000 pesos, interactions of distance to university of less than 20km with parental income and low expected return interacted with parental (per capita) income.

Table 4: Excess Responsiveness of the Poor to Changes in Direct Costs (Distance to College).

Dep. Var.: Attend College	Model 7	Model 8	Model 9
	Marg. Eff./(S.E.)	Marg. Eff./(S.E.)	Marg. Eff./(S.E.)
Univ 20 - 40km * Par Inc/Wealth Q1	-0.123**	-0.124**	-0.145*
	(0.054)	(0.053)	(0.075)
Univ 20 - 40km * Par Inc/Wealth Q1 * High Exp Ret			0.023
			(0.148)
Univ 20 - 40km * Par Inc/Wealth Q2	-0.009	-0.006	0.014
	(0.073)	(0.073)	(0.109)
Univ 20 - 40km * Par Inc/Wealth Q2 * High Exp Ret			-0.042
			(0.136)
Univ 20 - 40km * Par Inc/Wealth Q3	-0.078	-0.081	-0.064
	(0.062)	(0.060)	(0.095)
Univ 20 - 40km * Par Inc/Wealth Q3 * High Exp Ret			-0.018
			(0.141)
Univ 20 - 40km * Par Inc/Wealth Q4	0.074	0.071	0.116
	(0.073)	(0.072)	(0.109)
Univ 20 - 40km * Par Inc/Wealth Q4 * High Exp Ret			-0.065
			(0.115)
Univ > 40km * Par Inc/Wealth Q1	-0.064	-0.064	-0.020
	(0.053)	(0.052)	(0.078)
Univ > 40km * Par Inc/Wealth Q1 * High Exp Ret			-0.127
			(0.096)
Univ > 40km * Par Inc/Wealth Q2	-0.030	-0.030	-0.029
	(0.072)	(0.071)	(0.102)
Univ > 40km * Par Inc/Wealth Q2 * High Exp Ret			-0.006
			(0.147)
Univ > 40km * Par Inc/Wealth Q3	-0.178***	-0.177***	-0.214**
	(0.058)	(0.057)	(0.085)
Univ > 40km * Par Inc/Wealth Q3 * High Exp Ret			0.106
			(0.235)
Univ > 40km * Par Inc/Wealth Q4	-0.088	-0.087	-0.177**
	(0.064)	(0.063)	(0.076)
Univ > 40km * Par Inc/Wealth Q4 * High Exp Ret			0.266
			(0.188)
Interaction of Par Inc/Weath Quartiles and High Ret	Yes	Yes	Yes
Controls: Expected Return, Exp Log Earn,			
Prob of Work and Var of Log Earn	No	Yes	Yes
Controls: GPA, Par Inc/Wealth and Educ, Sex, State FE	Yes	Yes	Yes
Observations (Censored)	3342 (1730)	3342 (1730)	3342 (1730)
Log Likelihood	-2981.146	-2978.124	-2968.895
Sample Sel.: Corr. betw. Errors (P-Val)	-0.208 (0.488)	-0.177 (0.565)	-0.209 (0.504)

Notes: Table displays marginal effects and standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01. Excl. categories: male, lowest GPA tercile, parents' education primary or less, lowest parental income/wealth quartile, interactions of distance to university less than 20km with parental income/wealth and low expected return interacted with parental income/wealth quartiles.

Table 5: Excess Responsiveness of the Poor to Changes in Direct Costs (Tuition Costs).

Dep. Var.: Attend College	Model 10 Marg. Eff./(S.E.)	Model 11 Marg. Eff./(S.E.)	Model 12 Marg. Eff./(S.E.)
Tuition > 750 * Par Income < 5k	-0.043	-0.052	-0.010
	(0.040)	(0.040)	(0.058)
Tuition > 750 * Par Income < 5k * High Exp Ret			-0.124*
			(0.064)
Tuition > 750 * Par Income 5 - 10k	-0.013	-0.021	-0.053
	(0.055)	(0.055)	(0.075)
Tuition > 750 * Par Income 5 - 10k * High Exp Ret			0.039
			(0.108)
Tuition > 750 * Par Income > 10k	0.073	0.069	0.042
	(0.069)	(0.070)	(0.102)
Tuition > 750 * Par Income > 10k * High Exp Ret			0.021
			(0.127)
Par Income < 5k * High Exp Ret			0.099
			(0.062)
Par Income 5 - 10k * High Exp Ret			0.149*
			(0.086)
Par Income > 10k * High Exp Ret			0.131
			(0.093)
Controls for Expected Return, Exp Log Earn, Prob of Work and Var of Log Earn	No	Yes	Yes
Controls: GPA, Par Income and Educ, Sex, State FE	Yes	Yes	Yes
Observations (Censored)	3342 (1730)	3342 (1730)	3342 (1730)
Log Likelihood	-2987.347	-2975.075	-2969.499
Sample Sel.: Corr. betw. Errors (P-Val)	-0.268 (0.358)	-0.305 (0.297)	-0.280 (0.310)

Notes: Table displays marginal effects and standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01. Excl. categories: male, lowest GPA tercile, parents' education primary or less, per capita income less than 5000 pesos, interactions of tuition costs less than 750 pesos with parental income and low expected return interacted with parental (per capita) income.

Table 6: Excess Responsiveness of the Poor to Changes in Direct Costs (Tuition Costs).

Dep. Var.: Attend College	Model 13 Marg. Eff./(S.E.)	Model 14 Marg. Eff./(S.E.)	Model 15 Marg. Eff./(S.E.)
Tuition > 750 * Par Inc/Wealth Q1	-0.064 (0.048)	-0.067 (0.047)	-0.000 (0.071)
Tuition > 750 * Par Inc/Wealth Q1 * High Exp Ret			-0.148* (0.084)
Tuition > 750 * Par Inc/Wealth Q2	-0.037 (0.065)	-0.037 (0.064)	-0.006 (0.095)
Tuition > 750 * Par Inc/Wealth Q2 * High Exp Ret			-0.055 (0.118)
Tuition > 750 * Par Inc/Wealth Q3	-0.051 (0.062)	-0.055 (0.061)	-0.087 (0.094)
Tuition > 750 * Par Inc/Wealth Q3 * High Exp Ret			0.038 (0.137)
Tuition > 750 * Par Inc/Wealth Q4	0.069 (0.070)	0.066 (0.070)	0.117 (0.104)
Tuition > 750 * Par Inc/Wealth Q4 * High Exp Ret			-0.106 (0.101)
Interaction of Par Inc/Weath Quartiles and High Ret	Yes	Yes	Yes
Controls: Expected Return, Exp Log Earn, Prob of Work and Var of Log Earn	No	Yes	Yes
Controls: GPA, Par Inc/Wealth and Educ, Sex, State FE	Yes	Yes	Yes
Observations (Censored)	3342 (1730)	3342 (1730)	3342 (1730)
Log Likelihood	-2987.524	-2984.668	-2972.787
Sample Sel.: Corr. betw. Errors (P-Val)	-0.329 (0.236)	-0.309 (0.275)	-0.326 (0.247)

Notes: Table displays marginal effects and standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01. Excl. categories: male, lowest GPA tercile, parents' education primary or less, lowest parental income/wealth quartile, interactions of tuition costs less than 750 pesos with parental income/wealth and low expected return interacted with parental income/wealth quartiles.

Table 7: Counterfactual Policy Experiments.

Policy Change	Individuals Changing College Attendance Decision: Change in Overall Attendance Rate in pp (in %) (p-value)	Individuals Changing College Attendance Decision: **Marginal** Expected Return (MTE)	Individuals Attending College: **Average** Expected Return (TTE)	P-Value of One-Sided Test (MTE-TTE)
Decrease Dist by 20km				
for all	1pp (4%) (p-val 0.05)	0.91	0.71	0.18
for very poor	0.4pp (2%) (p-val 0.09)	0.92	0.71	0.25
for very poor and very able	0.2pp (1%) (p-val 0.07)	0.93	0.71	0.10
Decrease Tuition by 10%				
for all	0.4pp (2%) (p-val 0.39)	0.83	0.71	0.29
for very poor	0.3pp (1.5%) (p-val 0.28)	0.79	0.71	0.37
for very poor and very able	0.3pp (1.5%) (p-val 0.28)	0.81	0.71	0.36

Appendix B

Derivation of the Participation Equation

In order to use the potential outcome equations (2) and the subjective expectation information (3), and rewrite the participation equation in terms of expected returns to college, I use the following approximation

$$E(Y_{ia}) \equiv E(e^{\ln Y_{ia}}) \cong e^{E(\ln Y_{ia}) + 0.5Var(\ln Y_{ia})} \tag{15}$$

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 college earnings (analogously for high school earnings) as

$$\begin{aligned}
EPV_{18}(Y_i^1) &= \sum_{a=22}^{\infty} \frac{p_i^{W1} \exp(E_{18}(lnY_{ia}^1) + 0.5Var_{18}(lnY_{ia}^1))}{(1+r_i)^{a-18}} \\
&= \sum_{a=22}^{\infty} \frac{p_i^{W1} \exp\left(\alpha_1 + \beta_1' X_i + \gamma_1 p_i^{W1}(a-22) + \theta_1' f_i + 0.5(\sigma_i^1)^2\right)}{(1+r_i)^{a-18}} \\
&= \frac{p_i^{W1} \exp\left(\alpha_1 + \beta_1' X_i + \theta_1' f_i + 0.5(\sigma_i^1)^2\right)}{(1+r_i)^4} \cdot \left(\sum_{a=22}^{\infty} \frac{\exp\left(\gamma_1 p_i^{W1}(a-22)\right)}{(1+r_i)^{a-22}} \right) \\
&= \frac{p_i^{W1} \exp\left(\alpha_1 + \beta_1' X_i + \theta_1' f_i + 0.5(\sigma_i^1)^2\right)}{(1+r_i)^4} \left(\frac{1+r_i}{1+r_i - \exp(\gamma_1 p_i^{W1})} \right),
\end{aligned} \tag{16}$$

where I assume that $\exp(\gamma_j p_i^{Wj}) < 1 + r_i$ for $j = 0, 1$ to apply the rule for a geometric series,[29] and I use $A \to \infty$ as an approximation.

Data on subjective expectations of earnings for age $a = 25$ allow me to rewrite the expected present value of college earnings as follows (see equation (3)):

$$EPV_{18}(Y_i^1) = \frac{p_i^{W1} \exp\left(E_{18}(lnY_{i25}^1) + 0.5(\sigma_i^1)^2 - 3\gamma_1 p_i^{W1}\right)}{(1+r_i)^3} \cdot \left(\frac{1}{1+r_i - \exp(\gamma_1 p_i^{W1})} \right),$$

Analogously, I can derive the following expression for $EPV_{18}(Y_i^0)$

$$EPV_{18}(Y_i^0) = p_i^{W0} \exp\left(\alpha_0 + \beta_0' X_i + \theta_0' f_i + 0.5(\sigma_i^0)^2\right) \cdot \left(\frac{1+r_i}{1+r_i - \exp(\gamma_0 p_i^{W0})} \right). \tag{17}$$

An individual decides to attend college if $EPV_{18}(Y_i^1) - EPV_{18}(Y_i^0) - \frac{C_i}{p_i^C} \geq 0$, and thus if

[29] Some back-of-the-envelope calculations suggest that this assumption is reasonable in the given context: Papers such as Connolly and Gottschalk (2006) and Heckman, Lochner, and Taber (1998) find returns to experience well below 0.05 for the US, while interest rates in Mexico are clearly significantly higher than 0.05 in the relevant period (see for example McKenzie (2006)).

$$\left[\frac{p_i^{W1}\exp\left(E_{18}(lnY_{i25}^1)+0.5(\sigma_i^1)^2-3\gamma_1 p_i^{W1}\right)}{(1+r_i)^3}\cdot\left(\frac{1}{1+r_i-\exp(\gamma_1 p_i^{W1})}\right)\right]$$
$$-\left[p_i^{W0}\exp\left(E_{18}(lnY_{i25}^0)+0.5(\sigma_i^0)^2-7\gamma_0 p_i^{W0}\right)\cdot\left(\frac{1+r_i}{1+r_i-\exp(\gamma_0 p_i^{W0})}\right)\right]-\frac{C_i}{p_i^C}\geq 0,$$

which I can rewrite in the following way

$$\begin{aligned}\exp\left(E_{18}(lnY_{i25}^1)+0.5(\sigma_i^1)^2\right)-\exp\left(E_{18}(lnY_{i25}^0)+0.5(\sigma_i^0)^2\right)\\ \cdot\left[(1+r_i)^4\frac{p_i^{W0}}{p_i^{W1}}\cdot\frac{\exp(3\gamma_1 p_i^{W1})}{\exp(7\gamma_0 p_i^{W0})}\left(\frac{1+r_i-\exp(\gamma_1 p_i^{W1})}{1+r_i-\exp(\gamma_0 p_i^{W0})}\right)\right]\\ \geq (1+r_i)^3\frac{C_i}{p_i^C p_i^{W1}}(1+r_i-\exp(\gamma_1 p_i^{W1}))\end{aligned}$$

Assumption: $\left(\frac{1+r_i-\exp(\gamma_1 p_i^{W1})}{1+r_i-\exp(\gamma_0 p_i^{W0})}\right)\approx 1$, which is approximately satisfied given estimates of returns to experience of around 0.03 for college and 0.02 for high school and an interest rate of around 10% (see, for example, as mentioned above Connolly and Gottschalk (2006) using SIPP data for the US or Heckman, Lochner, and Taber (1998) who show that differences in returns to experience between high school and college educated are small).

In order to express the decision rule (18) in terms of expected gross returns to college and use the information on expected returns from 'subjective' expectations of earnings (see expression (4)), 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

$$\begin{aligned}B-A &= \left(E_{18}(\ln Y_{i25}^1)+0.5(\sigma_i^1)^2\right)-\left(E_{18}(\ln Y_{i25}^0)+0.5(\sigma_i^0)^2\right)\\ &= \rho_{i25}+0.5\left((\sigma_i^1)^2-(\sigma_i^0)^2\right),\end{aligned}$$

I can write the decision rule as

$$\exp\left(E_{18}(\ln Y_{i25}^0)+0.5(\sigma_i^0)^2\right)\cdot\left(\sum_{j=0}^{\infty}\frac{\left(\rho_{i25}+0.5\left((\sigma_i^1)^2-(\sigma_i^0)^2\right)\right)^j}{j!}\right)$$
$$-\left(\exp(E_{18}(\ln Y_{i25}^0)+0.5(\sigma_i^0)^2)\right)\cdot(1+r_i)^4\frac{p_i^{W0}}{p_i^{W1}}\cdot\frac{\exp(3\gamma_1 p_i^{W1})}{\exp(7\gamma_0 p_i^{W0})}-(1+r_i)^3\frac{C_i}{p_i^C p_i^{W1}}(1+r_i-\exp(\gamma_1))\geq 0.$$

Rearranging will lead to

$$\left(\sum_{j=0}^{\infty}\frac{\left(\rho_{i25}+0.5\left((\sigma_i^1)^2-(\sigma_i^0)^2\right)\right)^j}{j!}\right)-(1+r_i)^4\left[\frac{p_i^{W0}}{p_i^{W1}}\cdot\frac{\exp(3\gamma_1 p_i^{W1})}{\exp(7\gamma_0 p_i^{W0})}+\frac{C_i}{p_i^C p_i^{W1}\exp\left(E(\ln Y_{i25}^0)+0.5(\sigma_i^0)^2\right)}\right]$$
$$+(1+r_i)^3\frac{C_i}{p_i^C p_i^{W1}\exp\left(E(\ln Y_{i25}^0)+0.5(\sigma_i^0)^2\right)}\exp(\gamma_1 p_i^{W1})\geq 0.$$

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

$$\begin{aligned}
S^* &= \left(\sum_{j=0}^{\infty} \frac{\left(\rho_{i25} + 0.5\left((\sigma_i^1)^2 - (\sigma_i^0)^2\right)\right)^j}{j!} \right) \\
&\quad -(1+r_i)^4 \left[\frac{p_i^{W0}}{p_i^{W1}} \cdot \frac{\exp(3\gamma_1 p_i^{W1})}{\exp(7\gamma_0 p_i^{W0})} + \frac{C_i}{p_i^C p_i^{W1} \exp\left(E(\ln Y_{i25}^0) + 0.5(\sigma_i^0)^2\right)} \right] \\
&\quad +(1+r_i)^3 \frac{C_i}{p_i^C p_i^{W1} \exp\left(E(\ln Y_{i25}^0) + 0.5(\sigma_i^0)^2\right)} \exp(\gamma_1 p_i^{W1}) \geq 0. \\
S &= 1 \text{ if } S^* \geq 0 \\
S &= 0 \text{ otherwise,}
\end{aligned} \tag{18}$$

where S is a binary variable indicating the treatment status.

Derivation of the Testable Prediction of Excess Responsiveness

Making use of the participation equation for college attendance (see equation (18)), the following results show that individuals who face a higher interest rate are more responsive to changes in direct costs.

$$\frac{\partial S^*}{\partial C} = \frac{-(1+r_i)^4 + (1+r_i)^3 \exp(\gamma_1 p_i^{W1})}{p_i^C p_i^{W1} \exp\left(E(\ln Y_{i25}^0) + 0.5(\sigma_i^0)^2\right)} < 0$$

as $\exp(\gamma_1 p_i^{W1}) < 1 + r_i$ (see the previous section). Furthermore

$$\frac{\partial^2 S^*}{\partial C \partial r} = \frac{-4(1+r_i)^3 + 3(1+r_i)^2 \exp(\gamma_1 p_i^{W1})}{p_i^C p_i^{W1} \exp\left(E(\ln Y_{i25}^0) + 0.5(\sigma_i^0)^2\right)} < 0, \tag{19}$$

as $4(1+r_i) > 3\exp(\gamma_1 p_i^{W1})$.

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

Participation Equation as a Fourth-Order Polynomial in the Interest Rate

The participation equation (18) can be expressed as polynomial in the interest rate (so that r is left as the unobservable)

$$(1+r)^4 - (1+r)^3 \frac{C\exp(\gamma_1)}{\left(p_i^C p_i^{W1} \exp\left(E(\ln Y_{i25}^0) + 0.5(\sigma_i^0)^2\right)\right) \cdot \frac{p_i^{W0}}{p_i^{W1}} \cdot \frac{\exp(\gamma_1 3)}{\exp(\gamma_0 7)} + C}$$

$$- \left(\sum_{j=0}^{\infty} \frac{\left(\rho_i + 0.5\left((\sigma_i^1)^2 - (\sigma_i^0)^2\right)\right)^j}{j!} \right) \frac{p_i^C p_i^{W1} \exp\left(E(\ln Y_{i25}^0) + 0.5(\sigma_i^0)^2\right)}{\left(p_i^C p_i^{W1} \exp\left(E(\ln Y_{i25}^0) + 0.5(\sigma_i^0)^2\right)\right) \cdot \frac{p_i^{W0}}{p_i^{W1}} \cdot \frac{\exp(\gamma_1 3)}{\exp(\gamma_0 7)} + C} \leq 0.$$

Derivation of the Marginal Return to College

Derivation of equation (12):

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

Appendix C

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). This attendance rate is significantly lower than in many other Latin American countries (see Table 8). Mexico is characterized by large inequalities in access to college education for different income groups. In comparison to other Latin American countries, such as Colombia, Argentina and Chile, only Brazil has a smaller fraction of poor students attending college (see Table 8). Figure 9 displays college attendance rates of 18 to 24 year old high school graduates for different parental income quartiles.[30] High school graduates are already a selective group, for example for urban Mexico about 75% of the relevant age group attain a high school degree. The attendance rate of high school graduates 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. 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 10, 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, costs for transport and/or room and board, health insurance (mandatory for some universities), costs for schooling materials such as books. 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 3.4). Fifty 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 she can live with her family during college. I therefore construct a measure of distance to the closest university for each individual (see section 3.4).

In Mexico funding for higher-education fellowships and student loan programs is very limited

[30] Parental income is measured in the last year before the college attendance decision.

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 8). 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 three conditions: first, a maximum level of family income, where priority is given to families with less than two times the minimum monthly salary, while in special cases people are still eligible with less than four times the minimum monthly salary. Second, students need a minimum GPA (80) and third, they have to have 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 program, SOFES, offers loans to 1.5% of students and was implemented by a collaboration of private universities. It is need-and-merit based, but students with collateral are preferred. The other three are very small state programs, ICEES in Sonora state, ICEET in Tamaulipas, and Educafin in Guanajuato, which are not part of my sample.

Figure 9: College enrollment rates of 18 to 24 year old high school completers by parental income quartile (Mexican Family Life Survey, 2003).

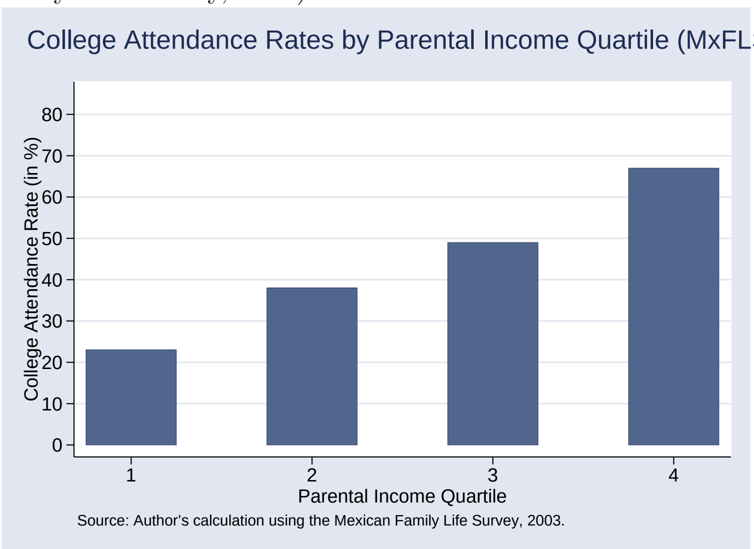

Figure 10: College enrollment rates of 18 to 24 year old high school completers by parental income quartile (Jovenes con Oportunidades Survey, 2005).

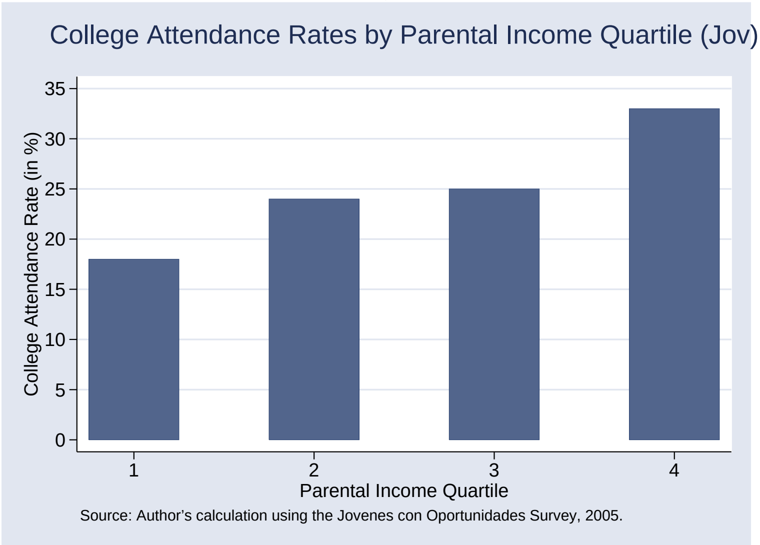

Table 8: Comparison of enrollment rates, fraction of poorest 40% in percent of the student population, fraction of GDP spend on higher education, fraction of expenditures on higher education on fellowships and student loans: Mexico, other Latin American countries, OECD and USA.

Countries Ranked by Per Cap GDP	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	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 ".".

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 adolescents between age 15 and 25 using the "Jovenes" (youth) questionnaire. If the adolescent was not present, the household head or spouse answered the Jovenes questionnaire as well. As a result the questions on expected earnings were not answered by the adolescent herself for about half the sample, i.e. mothers state their expectations about future earnings of her child(ren) that are not present during the interviewer's visit.

Table 9 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: for example, adolescent respondents live significantly closer to the closest university and are significantly more likely to be female (as many families do not want their female children to live on their own away from home). On the other hand, variables such as expected returns to college as well as GPA, father's years of schooling and per capita parental income do not differ significantly between the two groups.

Table 9: Summary statistics of important variables of the two groups of respondents.

Respondent	Adolescent Mean (SE)	Mother Mean (SE)	P-Val of Diff
Expected Return	0.6670	0.6550	0.347
	(0.3820)	(0.3592)	
Expected Log High School Earnings	7.5778	7.6477	0.000
	(0.5004)	(0.4338)	
Var of Log High School Earnings	0.0054	0.0046	0.003
	(0.0079)	(0.0062)	
Var of Log College Earnings	0.0039	0.0034	0.022
	(0.0061)	(0.0054)	
Prob of Work High School	0.6657	0.6505	0.015
	(0.1817)	(0.1780)	
Prob of Work College	0.8250	0.8142	0.046
	(0.1601)	(0.1544)	
College Attendance Rate	0.2308	0.3636	0.000
	(0.4215)	(0.4812)	
Female	0.5813	0.4954	0.000
	(0.4935)	(0.5001)	
GPA (Scale 0 to 100)	82.19	82.27	0.783
	(7.16)	(10.34)	
Father's Yrs of Schooling	5.33	5.34	0.902
	(2.96)	(3.03)	
Mother's Yrs of Schooling	5.03	5.06	0.794
	(2.77)	(2.76)	
Per Capital Parental Income (Pesos)	7519.54	7925.42	0.371
	(8010.08)	(13638.29)	
Distance to University (km)	24.2312	26.4647	0.005
	(22.8159)	(22.8688)	
Tuition Costs (Pesos)	608.8104	503.4896	0.000
	(634.5729)	(338.1346)	

Table 10: Probit Model for College Attendance: First Stage Results

	Marg. Eff./(S.E.)	Marg. Eff./(S.E.)
Interview Sunday (d)	0.110*	0.092
	(0.059)	(0.061)
Interview Thursday (d)	-0.087**	-0.089**
	(0.037)	(0.038)
Interview Thursday*Aftern. (d)	0.079*	0.067
	(0.042)	(0.043)
Interview Saturday*Aftern. (d)	0.106**	0.114**
	(0.052)	(0.053)
Interview Saturday*Even. (d)	0.285***	0.336***
	(0.083)	(0.074)
Interview Week 40 (d)	0.149**	0.144**
	(0.060)	(0.061)
Interview Week 41 (d)	0.133***	0.160***
	(0.032)	(0.032)
Interview Week 42 (d)	0.112***	0.117***
	(0.028)	(0.029)
Interview Week 45 (d)	-0.053**	-0.070**
	(0.026)	(0.027)
Interview Week 46 (d)	-0.047	-0.077**
	(0.037)	(0.038)
Female (d)		0.102***
		(0.018)
GPA - top tercile (d)		-0.089***
		(0.021)
Father's Educ - Jr HS (d)		-0.036
		(0.029)
Father's Educ - Sr HS (d)		-0.005
		(0.056)
Father's Educ - Univ (d)		-0.154
		(0.102)
Mother's Educ - Univ (d)		0.285**
		(0.143)
Per cap Income - 5 to 10k (d)		-0.012
		(0.022)
Per cap Income - more than 10k (d)		0.017
		(0.025)
Dist to Univ 20 to 40km (d)		0.022
		(0.022)
Dist to Univ above 40km (d)		-0.016
		(0.026)
Tuition Above 750 Pesos (d)		-0.011
		(0.030)
State FE	Yes	Yes
Observations	3342	3342
Log Likelihood	-2264.413	-2172.746
P-value	0.000	0.000

Notes: Table displays marginal effects and standard errors in brackets. * $p<0.1$ ** $p<0.05$ *** $p<0.01$. Excl. categories: Interview on Monday, Interview in the morning, Interview in week 43, male, lowest GPA tercile, parents' education primary or less, per capita income less than 5000 pesos. GPA second tercile and mother's education lower than university not displayed due to space constraints (not significant).

Robustness Checks

Table 11: Correlation between Expected Returns and Direct Costs of Schooling.

Dep Var: Expected Return	Coeff./(S.E.)	Coeff./(S.E.)
Mother's Educ - Jr HS	-0.009	0.011
	(0.034)	(0.030)
Mother's Educ - Sr HS	0.048	0.036
	(0.076)	(0.073)
Mother's Educ - Univ	0.168	0.115
	(0.192)	(0.158)
Father's Educ - Jr HS	0.001	0.027
	(0.035)	(0.032)
Father's Educ - Sr HS	0.066	0.054
	(0.061)	(0.058)
Father's Educ - Univ	-0.186	-0.054
	(0.144)	(0.136)
Per cap Income - 5 to 10k	0.022	-0.002
	(0.028)	(0.023)
Per cap Income - more than 10k	-0.007	-0.007
	(0.031)	(0.027)
GPA - second tercile	0.004	0.026
	(0.027)	(0.023)
GPA - top tercile	0.042	0.053**
	(0.028)	(0.024)
Distance to University	0.002	
	(0.002)	
Distance Squared	-0.000	
	(0.000)	
Tuition Costs	0.000	
	(0.000)	
Tuition Squared	0.000	
	(0.000)	
Tuition Above 750 Pesos		0.046
		(0.031)
Dist to Univ 20 to 40km		0.013
		(0.023)
Dist to Univ above 40km		0.043
		(0.028)
Observations	2327	3342
Censored Observations	1156	1730
Lambda	-0.086	-0.070
S.E. of Lambda	0.063	0.064

Notes: * $p<0.1$ ** $p<0.05$ *** $p<0.01$. Excl. categories: male, lowest GPA tercile, parents' education primary or less, per capita income less than 5000 pesos.