International Child Sponsorship Impact on the Intended Choice of Acquiring a Higher Education Degree: the Case of Rural Mexico

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Abstract

This paper studies the impact of a child sponsorship program on the aspiration to acquire a higher education degree, among a sample of rural children in the states of Oaxaca and Chiapas in the south of Mexico. To account for the program's selection of sponsored children, I estimate a binary Roy type model with unobservables generated by a one-factor structure. I further account for the children's income beliefs by directly eliciting their subjective expected returns to schooling. I find that the average treatment effect on the treated is positive and consistent with previous studies of the sponsorship program, although it is not statistically significant. Estimates of the marginal treatment effect show that the sponsorship effect is higher for children most likely to be selected to the program. From the subjective income expectations data, I document that children in rural settings, 12 to 15 years old, have realistic although heterogeneous expectations, and present a clear gender gap, even at these young ages.

1 Introduction

Despite large returns to education, impoverished regions in Latin America still present very low levels of schooling. In two of the most socio-economically marginalized states in Mexico, Oaxaca and Chiapas, the average years of education for adults older than 24 are 7.5 and 7.2, just one year above primary school. It is well established that the presence of external constraints, such as the lack of income and poor health, is detrimental for the development of children[1]. Nevertheless, a growing body of research also emphasizes the importance of internal constraints, such as the lack

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[1] An example of a successful program that alleviated external constraints was *Prospera* (previously known as *Oportunidades*), a conditional cash transfer program with high and positive effects in the level of education (Todd and Wolpin, 2006; Attanasio et al., 2012), but which was controversially discontinued by the current Mexican administration.

of grit, perseverance, self-control, self-esteem, and aspirations, which are important inhibitors of the development of children and youth (Cunha and Heckman, 2009; Heckman and Kautz, 2012; Heckman, Pinto and Savelyev, 2013; Dalton et al., 2016).

In this paper, I study the impact of a child sponsorship program, Compassion International (from now on CI), which has a holistic view of the children's development. International child sponsorship programs serve as means to transfer direct resources from individuals in developed countries, to impoverished children in developing countries. Programs like Compassion International also focus on the relief of internal constraints through the development of the children's socio-emotional skills. In this study, I analyze Compassion's impact on the educational aspirations among its participants, measured by the revealed intended choice of acquiring a technical or college degree.

It is important to study the impact of programs with a more holistic treatment. The socio-emotional skills children develop at younger ages can have lifelong effects, and yet, our understanding of these type of programs is limited[2]. Furthermore, it is important to understand how to alleviate internal constraints at younger ages both because they can exacerbate external constraints in the future and because such constraints are more malleable at younger ages (Borghans et al., 2006).

I find that the average treatment effects on the treated are positive and consistent with previous studies of the sponsorship program, although they are not statistically significant. Estimates of the marginal treatment effect show that the sponsorship effect is positively correlated with selection to the program, that is, the sponsorship is higher for those most likely to be selected to participate. From the subjective expectations data, I document that children, as young as 12 to 15 years old, have realistic although heterogeneous expectations. Even from these young ages, I find a clear gender gap in earnings expectations.

This paper complements recent studies of CI that have looked at the effect of the program both on observed adult outcomes and on children's psychological indices. In early work, Wydick et al., (2013) found long term impacts of sponsorship by CI in school attainment (1.03 - 1.46 years), and on the probability of acquiring a white-collar job (6.6 percent). More recently, Glewwe et al., (2017) use children's self-portraits in Indonesia to study the impact of sponsorship on the children's levels of hope, happiness, and self-efficacy and find positive effects in the order of 0.66, 0.42 and 0.29 standard deviations of normalized indexes of the respective variables. Likewise, Ross et al., (2020) study CI's impact in Kenya, Indonesia, and Mexico on further normalized psychological indices: self-esteem, aspirations, and optimism. Over the three countries, the authors find sponsorship

[2]For recent studies, see Heckman and Kautz (2012) and Heckman et al., (2013) who study how the Perry Preschool Project may have been instrumental in the development of psychological factor of young children, and how this effects may have accrued in better outcomes during adulthood.

effects of 0.25, 0.26, and 0.29 standard deviations. We contribute to the above in two important ways. We first add more structure to the estimation of the sponsorship effect to account for the selection procedure of the sponsored children. Second, the added structure allows us to estimate the marginal treatment effect, which in turn lets us see how the selection to sponsorship correlates with the treatment effect.

To account for the selection procedure, we use a binary Roy type model with a one-factor structure to further control for selection on unobservables. The results of Aakvik et al., (2005), as described in Section 4, allow the estimation of the average treatment effect $ATE(x)$, the treatment on the treated $TT(x)$, and the marginal treatment effect $MTE(x)$ for different groups.

This paper additionally contributes to two additional strands of literature. First, the importance of subjective expectations in shaping economic outcomes. To predict the intended choice of schooling, we elicit income expectations data to estimate the perceived returns to education, similar to Jensen (2010), Nguyen (2008), Attanasio and Kaufman (2009), Kaufman (2014) and Stinebrickner and Stinebrickner (2012, 2014). Second, the paper relates to a growing literature that uses the stated school choice within discrete choice models. Beliefs about educational future choices are one of the most important predictors of realized choices, above other standard determinants of schooling (Jacob and Wilder, 2011; Beaman et al., 2012). Recently, stated school choices have been used to study the choice of the level of schooling (Delavende and Zafar, 2017), and the choice of a major (Arcidiacono, 2004; Arcidiacono et al., 2017, Zafar, 2013; Wiswall and Zafar, 2015).

The rest of the paper proceeds as follows, I first introduce CI's institutional framework, along with a description of both the selection procedure of the sponsored children, and the benefits they receive. Second, a description of the fieldwork and data collection follows, specifically the module on subjective expectations. Next, I specify the model and the estimation of the sponsorship effect on the population, and on the sponsored individuals. Finally, I discuss the results and conclude.

2 Institutional framework

Compassion International (CI) is the third largest child sponsorship program in the world, sponsoring around 1.3 million children throughout 26 countries. CI is a faith-based, nonprofit organization that partners with local churches to carry its programming. The staff is local, and foreign workers are rare.

The benefits sponsored children receive vary little between countries. Mainly, the sponsored children participate in structured programs after school that emphasize their spiritual, physical and socio-emotional development[3], and receive in-kind income transfers. In practice, this means

[3] In Mexico, the program lasts between five to six hours per week, and it takes place during the weekend.

that the students receive academic tutoring, school supplies, and uniforms, classes that emphasize the spiritual and socio-emotional development of the child, health care in the form of general examinations by local nurses and doctors affiliated with CI, and a catastrophic health insurance. The usual sponsorship lasts until secondary school, but some receive support even during university through a leadership development program. In a large study of CI conducted over six different countries by Wydick et al., (2013), the average duration of sponsorship was 9.3 years, which accounts approximately for 4,000 hours of programmed activities for each sponsored child. CI has a large presence in Mexico, with 33,360 children participating in more than 185 child development centers.

In Mexico, to select the children for sponsorship, CI first selects the poorest communities among the poorest regions of a country. Within a community, they partner with a local church to conduct their programming. After CI opens a program in a community, the local staff recruits the neediest households from their community, and finally, the parents select the children that will be sponsored, provided they meet the following criteria[4]:

- The household where the child lives is no further than 30 minutes walking distance from a CI center.
- The child is not receiving sponsorship through another organization.
- There must not be more than three sponsored children per household.
- The children must be 9 or younger to start receiving sponsorship. After age 10, the children are not eligible to start receiving sponsorship. Also, children close to 9 years old receive lower priority[5].

Preference is given to orphans, refugees, and children that live with a widowed parent or family member. Finally, although CI partners with churches to conduct its programming, CI does not discriminate based on religious background. Nevertheless, the family must allow the children to attend the program activities, which most of the time take place at the church.

[4]Compassion International is present globally, and although both the selection procedure and benefits provided are quite homogeneous, some differences might arise between countries. For example, in Indonesia, the program sponsored up to two children per family.

[5]This restriction has been updated since we gathered the data. CI now prioritizes the sponsorship of children younger than 3 years old.

3 Fieldwork and Data

We implemented our survey work from June to August of 2017, in the states of Oaxaca and Chiapas in the south of Mexico[6]. In Mexico, we surveyed eight communities, four with a CI project and four without one. The CI sites were randomly selected from rural settings in Oaxaca and Chiapas, of which one was selected from the state of Oaxaca and three from Chiapas. A nearby community for each compassion site was selected based on similarity given observables. Importantly, the nearby sites had the same educational and health institutions, that is, each site had only one primary school, one middle school, one high-school, and only one health post for basic care.

We surveyed the sponsored children at their households, along with their next oldest and next youngest sibling provided they were between 10 to 18 years old. Within the sites with a sponsorship program, we also surveyed households where none of its members were sponsored. We randomly selected the non-sponsored households and surveyed all members between 10 to 18 years old.

In each community, the sampling of the non-sponsored households proceeded as follows. After randomly choosing a starting point in the village, we selected every second household on the street for possible inclusion in the survey. When the end of the street or block was reached, the enumerators turned left and continued with every second household, then they turned right and proceeded in the same way. The household was briefly questioned to see if any member was between 10 to 18 years old, and we proceeded if there was a member that met the age criteria. Some surveyed individuals had siblings living in other parts of the village or other communities. We tried to reach such individuals provided we had approval from their parents.

We gathered data on demographic characteristics, educational attainment, desired level of education, variables of self-esteem based on Rosenberg (1965), and other constructs such as optimism and social trust. For the level of income, since we did not survey the parents, we asked the children for household assets in order to build an asset index as an approximate for income, following Filmer and Pritchett (2001)[7]. Finally, in order to elicit the expected returns to education, we use data on subjective expectations, which we explain in more detail in the following section.

The initial sample consisted of 926 individuals aged 10 to 18. Given our use of expected income, and given that children in rural areas usually start to work after primary school when they are aged 12, we use only the data for the individuals aged 12 or older. Furthermore, the CI sites had, in general, less than 6 years since they started their operations, so we further restricted the sample to the individuals aged 12 to 15. Recall that the age eligibility criteria requires children to be nine or younger to receive sponsorship, so the oldest sponsored children in our sample were aged 15. We

[6] The fieldwork was conducted as part of a larger evaluation of CI. A companion paper, Ross et al., (2020) studies CI's impact on psychological variables, and their mediation on schooling outcomes

[7] The authors build the asset index using the first principal component.

are left with a sample of 403 children, 163 sponsored, and 240 in the control group. Furthermore, for some parts of the analysis, we restricted the sample to the individuals that correctly interpreted the probability questions.

Table 1: Summary statistics: sponsored vs non-sponsored

	Mean all (S.D.)	Sponsored (S.D.)	Non-Sponsored (S.D.)	t-test (S.E.)
Higher education[1]	0.730	0.712	0.742	-0.030
	(0.445)	(0.454)	(0.439)	(0.045)
University[1]	0.620	0.571	0.654	-0.084*
	(0.486)	(0.497)	(0.477)	(0.050)
Age	13.375	13.006	13.625	-0.619***
	(1.105)	(1.003)	(1.102)	(0.102)
Male	0.469	0.429	0.496	-0.066
	(0.500)	(0.497)	(0.501)	(0.050)
Birth order	2.495	2.441	2.532	-0.091
	(1.740)	(1.635)	(1.810)	(0.195)
Num. siblings	3.930	3.945	3.919	0.025
	(2.019)	(2.088)	(1.974)	(0.229)
Protestant	0.506	0.730	0.354	0.376***
	(0.501)	(0.445)	(0.479)	(0.049)
Prospera	0.868	0.871	0.867	0.004
	(0.338)	(0.336)	(0.341)	(0.035)
Education father	6.797	7.000	6.659	0.341
	(3.207)	(3.006)	(3.336)	(0.356)
Education mother	6.490	6.321	6.604	-0.283
	(3.161)	(3.283)	(3.077)	(0.346)
Asset index	0.057	-0.216	0.244	-0.460***
	(1.561)	(1.516)	(1.566)	(0.152)
N	403	163	240	403

*** p<0.01, ** p<0.05, * p<0.1

[1] Denote that the child expects to achieve higher education or university, respectively.

Demographic characteristics by sponsorship status are presented in Table 1. Both groups were constrained to ages between 12 to 15, nevertheless, differences arise in age, as well as in religion and in the asset index. These differences are consistent with CI's selection criteria, where we would expect younger and poorer children to be more likely to be selected. Apart from these variables, we do not find statistically significant differences in the rest of the demographic factors. For a more desegregated summary see Tables 5 and 6 in the Appendix, where we divide the data by the sponsorship status of children, separating the sponsored from the non-sponsored siblings of sponsored children, the non-sponsored children from non-sponsored households in a community with CI, and households in communities without the presence of CI. The observations remain the same. Also in the Appendix in Table 7, we compare the individuals by community.

3.1 Subjective expectations data and estimation of the returns to schooling

Observed choices may be consistent with different specifications of preferences and expectations, so researchers commonly assume particular sorts of expectations. The measurement of these expectations could avoid this identification problem (Manski, 2004).

The use of subjective expectations is becoming more common, and their use has been applied for a wide array of topics, which include: income expectations (Dominitz and Manksi, 1997), social security expectations (Bernheim, 1998; Gustman and Steinmeier, 1999, 2001), mutual fund investments (Dominitz and Manski, 2003, 2004), probabilistic polling (Manski, 1990), and students' expectations of the returns to schooling (Dominitz and Manski, 1996; Nguyen, 2008; Attanasio and Kaufman, 2013; Jensen, 2010; Kaufman, 2014, Stinebrickner and Stinebrickner, 2014; Zafar, 2011, 2013). For a review see Attanasio (2009) and Delavende et al., (2011).

In this study, I elicit subjective expectations on the returns to schooling, following a similar procedure used in an evaluation of *Prospera* (previously known as *Oportunidades*), a well known conditional cash transfer program in Mexico. In 2002/03, an additional program called *Jóvenes con Oportunidades*, was introduced as part of *Oportunidades*, and subjective expectations data was collected in 2005. I use the same module here.

First, each individual was asked about the probability of working conditional on different schooling scenarios.

- Assume that you finish (*level of education*) and that this is your highest schooling degree. From 0 to 100, how certain are you that you will be working at the age of 25?

Then, the questions on earnings subjective expectations, conditional on a schooling level and on being employed, are the following:

- Assume that you finish (*level of education*) 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 0 to 100, what is the probability that your earnings at that age will be at least x, where $x = (\frac{max+min}{2})$?

This question was asked for five levels of education: primary school, middle school, high-school, technical studies and university. Following Atanassio and Kaufman (2013) who use the data on *Oportunidades*, we form the returns to education from the previous questions. Let Y^ℓ be the level of income with level of education ℓ. We are interested in the subjective distributions of future earnings $f(Y^\ell)$, where ($\ell = 1$) for primary school,($\ell = 2$) for middle-school, ($\ell = 3$) for high-school, ($\ell = 4$) for technical studies, and ($\ell = 5$) for college. Given that the survey asks for the maximum and the minimum of expected income for each level of education, we have the support of the distribution for each individual $[y^\ell_{min}, y^\ell_{max}]$, furthermore, we know $p = Pr(Y^\ell > y^\ell_{mid})$, for $y^\ell_{mid} = (y^\ell_{min} + y^\ell_{max})/2$. Thus, assuming a triangular distribution for $f(\cdot)$, we can estimate the expected value of the log of future earnings for each individual and level of education ($\ell = 1, ..., 5$), by:

$$E[ln(Y^\ell)] = \int_{y_{min}}^{y_{max}} ln(y) f_{Y^\ell}(y) dy.$$

Using these results, we can directly estimate the expected returns to schooling:

$$\rho^\ell = E[ln(Y^\ell)] - E[ln(Y^{\ell-1})], \text{ for } \ell = 2, 3, 4, 5.$$

3.2 Validity check of the subjective expectations data

Given that I have cross-section data, I can only compare the subjective expectation with historical recordings, as opposed to comparing the expectations to realizations. Additionally, in this specific case, I can directly compare the subjective expectations to those from the survey on *Prospera* from 2005, as reported by Attanasio and Kaufman (2004). As mentioned before, I am using the same question as in the *Prospera* survey, and furthermore, 85 percent of our sample consists of households that receive *Prospera*.

Notice that differences between the subjective expectations data and historical realizations do not necessarily mean that the subjective expectations are not valid. It is actually the fact that they may differ that we are interested in measuring them. The perceived expected returns to education matter for school choice, as it is the perceived return that may affect choices.

Next, I describe how the earnings subjective expectations compare to census data of 2015 at 2017 prices. Table 2 displays the median of the data by gender and locality, where the census data has been further divided between regions with a population greater or lower than 50 thousand[8]. Various patterns are of interest. First, the median of the expectations data does not show unreasonable deviations, with higher income expectation in the state of Oaxaca than in Chiapas, consistent with the census recordings. Second, we do observe higher levels compared to those reported by Attanasio and Kaufman (2014). In their sample of *Prospera* recipients, the individuals underestimated the

[8]The population groups are formed given constraints in the census data.

Table 2: Expected income vs census data at age 24 (median of data, MX pesos)

	High-school			Technical school			University		
	Male	Female	Total	Male	Female	Total	Male	Female	Total
Census									
Oaxaca less than	4271.7	3295.6	4119	5186.9	4271.7	4577.1	6407.6	6407.6	6407.6
50,000 residents	(4293.9)	(2577.1)	(3777.6)	(3296.6)	(2939.9)	(3123.7)	(3661.4)	(3058.3)	(3348.0)
Oaxaca more than	4577.1	3867.5	4271.7	7933.1	4577.1	4577.1	4698.9	5339.6	5339.6
50,000 residents	(4359.6)	(1691.5)	(3549.4)	(5394)	(2008.4)	(3220)	(3052.2)	(3231.6)	(3151.8)
Chiapas less than	3203.8	2745.6	3203.8	3753.2	2867.9	3661.9	5339.6	4577.1	4752.3
50,000 residents	(2749.4)	(2300)	(2655)	(4208.7)	(2646.5)	(3656.1)	(3504.8)	(3042)	(3304.2)
Chiapas more than	4271.7	3547.1	3844.5	6407.6	2563	5034.7	5339.6	5339.6	5339.6
50,000 residents	(2444.1)	(2397.4)	(2456.6)	(4876.8)	(3806.1)	(4372.2)	(27981.3)	(4658.4)	(20422.7)
Survey									
Oaxaca Sponsored	6765.6	2738.7	4411.2	9550.1	4216.8	6078	13110.3	5825.5	7712.8
	(4550.5)	(2974.5)	(3976.4)	(5557.4)	(4583.2)	(5322.2)	(8135.9)	(5865.4)	(7634.8)
Oaxaca Non-Sponsored	4245.8	3247.5	4001.2	5872.6	5223.1	5872.6	9762.5	6470.9	7737.9
	(4992.9)	(18417.2)	(13414.7)	(11393.9)	(20065.9)	(16025.6)	(16475.7)	(25780.8)	(21230.6)
Chiapas Sponsored	3605.3	3395.3	3484.3	4395.7	5560.3	5401.8	6815.7	8182.9	7737.9
	(8553.6)	(5440.1)	(6794.5)	(10896.8)	(6503.7)	(8454.8)	(16637.1)	(15539.1)	(15877.2)
Chiapas Non-Sponsored	3929.6	3619.4	3737.6	6161.7	5499.3	5547.8	8568.4	8575.3	8575.3
	(4554.8)	(3861.7)	(4195.5)	(8197.8)	(5905)	(7102.4)	(16785.5)	(10924.4)	(14050.3)
Attanasio and Kaufman (2004) - averages	3525.5	2509.3					6110.6	4806.8	

Standard deviations in parentheses.

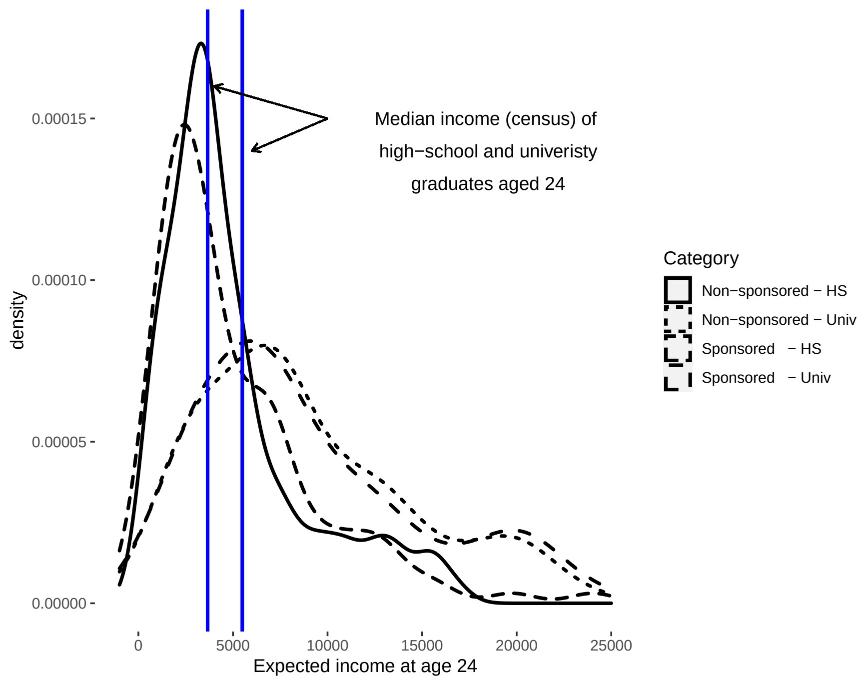
level of income compared to census data, whereas in our sample the students overestimated it. This difference could be explained by the difference in age between the samples, theirs is a sample of individuals between 15 and 25, and ours of 12 to 15. Also, ours is a smaller sample.

The third pattern in Table 2 is a clear gender gap in income expectations, even at the young ages of 12 to 15. Female individuals expect future income to be around 50 percent less than males in Oaxaca, and 8 percent in Chiapas with high-school and technical education. Interestingly, female youth have higher expectations than males given university studies in the state of Chiapas, nevertheless, this relationship is reversed when looking at the means. A table comparing the means rather then the medians can be found in the Appendix in Table 8.

To further describe the difference in earnings expectations, I plot in Figure 1 the sample distribution of the believed future income by sponsorship status for two levels of education: high-school and university. Both distributions present fat tails to the right, showing heterogeneous beliefs, but the modes are close to the census medians represented by the vertical lines. The first line represents the median income of high-school graduates at age 24, and the second line the median income of university graduates aged 24, in the states of Oaxaca and Chiapas. Additionally, a graph of income distribution by gender can be found in the Appendix in Figure 3.

We might be worried that children were not able to understand the probability question, or that they may have been overly optimistic. As a robustness analysis, I have estimated the expected income using a uniform distribution rather than triangular, where I do not use data on the probability questions. The results do not change much[9]. A distribution of the expected income using the uniform distribution, both by sponsorship status and gender, can be respectively found in Figures 4 and 5 in the Appendix.

Figure 1: Expected income distribution for high-school and university by sponsorship status



4 Model

To account for the selection of the sponsored children, I use a discrete choice latent index framework following Aakvik et al., (2005), and estimate a three equation model. The equations modeled are an outcome equation for the sponsored, an outcome equation for the non-sponsored, and a selection equation. Let S_i denote the sponsorship status, where $S_i = 1$ if the individual i is sponsored, and $S_i = 0$ otherwise. Let (Y_{1i}, Y_{0i}) be the two potential binary outcomes for individual i under sponsorship and non-sponsorship, where $Y_{1i} = 1$ if individual i is sponsored and reveals that her intended choice of schooling is higher education (i.e., acquiring a technical or college degree), and $Y_{1i} = 0$ if her intended choice of schooling is lower then higher education. Likewise, Y_{0i} is similarly

[9]We have also estimated the model (as explained in Section 4), with this estimate. The results do not vary much and are available upon request.

defined but for the non-sponsored. The observed outcome variable is $Y_i = S_i Y_{1i} + (1 - S_i)Y_{0i}$. We assume that a latent variable model generates S, such that:

$$S_i^* = \gamma_0 + age\_6_i\gamma_1 + age\_7_i\gamma_2 + age\_8_i\gamma_3 + asset\_index_i\gamma_4 + religion_i\gamma_5 + site\_CI_i\gamma_6 + U_{Si},$$
$$S_i^* = Z_i\gamma + U_{Si},$$
$$S_i = \begin{cases} 1 \text{ if } S_i^* > 0, \\ 0 \text{ otherwise,} \end{cases}$$

where Z_i is a vector of observed covariates, $\gamma = (\gamma_0, ..., \gamma_6)$ the set of parameters of the selection equation, and U_{Si} is an unobserved random variable to the econometrician. As exclusion restrictions, similar to Wydick et al., (2013), I use a set of dummy variables for the age of the individual when the CI project open in her community, here denoted as Age_p for $p = (6, 7, 8)$. Age_p is a dummy variable for the individuals that were "p" years old when the program started in the community. The omitted category is Age_9 or older. I also consider whether the children attend a protestant church, ($religion_i$), a dummy variable if the community has a CI program ($site\_CI_i$), and finally, an asset index using the first principal component of a set of household assets. As for the outcome equations of the intended choice of schooling, I again assume that they are generated by a latent variable. For the sponsored, we have:

$$Y_{1i}^* = \beta_0^1 + \rho_{HE,i}\beta_2^1 + Dist_i\beta_3^1 + \tilde{X}_i\beta_4^1 + U_{1i},$$
$$Y_{1i}^* = X_i\beta_1 + U_{1i},$$
$$Y_{1i} = \begin{cases} 1 \text{ if } Y_{1i}^* > 0, \\ 0 \text{ otherwise.} \end{cases}$$

Likewise, the outcome equation of the intended choice of schooling for the non-sponsored is:

$$Y_{0i}^* = \beta_0^0 + \rho_{HE,i}\beta_2^0 + Dist_i\beta_3^0 + \tilde{X}_i\beta_4^0 + U_{0i},$$
$$Y_{0i}^* = X_i\beta_0 + U_{0i},$$
$$Y_{0i} = \begin{cases} 1 \text{ if } Y_{0i}^* > 0, \\ 0 \text{ otherwise.} \end{cases}$$

Where $X_i = (1, \rho_{HE,i}, Dist_i, \tilde{X}_i)$ are observed covariates, $\beta_0 = (\beta_0^0, ..., \beta_4^0)$, and $\beta_1 = (\beta_0^1, ..., \beta_4^1)$ are the coefficients of the outcome equations, and U_{1i} and U_{0i} are unobserved random variables. Here $\rho_{HE,i}$ stands for the believed returns to higher education, which was elicited directly as explained in sub-section 3.1. $Dist_i$ stands for distance (in kilometers) to the closest public university, and $\tilde{X}_i$ is a set of other covariates such as gender, an asset index, and the parent's average years of education. Following Aakvik et al., (2005), I assume that the error terms U_{Si}, U_{1i}, U_{0i} follow a one factor structure:

$$U_{Si} = -\theta_i + \varepsilon_{Si},$$
$$U_{1i} = -\alpha_1\theta_i + \varepsilon_{1i},$$
$$U_{0i} = -\alpha_0\theta_i + \varepsilon_{0i}.$$

I further assume that $(\theta_i, \varepsilon_{Si}, \varepsilon_{1i}, \varepsilon_{0i})' \sim N(0, I)$ for all i. Notice that the normalization of $Var(\theta) = Var(\varepsilon_1) = Var(\varepsilon_0) = 1$ is without loss of generality for the estimation of the sponsorship effects. To estimate the model, conditional on θ, the likelihood of the model is:

$$\begin{aligned} L_i &= \prod_{i=1}^{N} Pr(S_i, Y_i|X_i, Z_i, \theta_i), \\ &= \prod_{i=1}^{N} Pr(Y_i|S_i, X_i, \theta_i) Pr(S_i|Z_i, \theta_i), \end{aligned}$$

where it can be shown that:

$$\begin{aligned} Pr(Y_i = 1|S_i = 1, X_i, \theta_i) &= \Phi(X_i\beta_1 + \alpha_1\theta_i), \\ Pr(Y_i = 1|S_i = 0, X_i, \theta_i) &= \Phi(X_i\beta_0 + \alpha_0\theta_i), \\ Pr(S_i = 1|Z_i, \theta_i) &= \Phi(Z_i\gamma + \theta_1). \end{aligned}$$

Given that we do not know θ, I integrate it out and form the likelihood.

$$L = \prod_{i=1}^{N} \int Pr(S_i, Y_i|X_i, Z_i, \theta)\phi(\theta)d(\theta).$$

From this model, we can identify $(\gamma, \beta_0, \beta_1)$ and (α_0, α_1), which can be estimated by maximum likelihood after integrating out θ[10]. Notice that this analysis rests on the normality assumption of θ. For a more flexible functional dependence of the response variable or continuous covariates, see Marra and Radice (2011).

4.1 Sponsorship effect estimation

Having estimated the parameters, $(\hat{\gamma}, \hat{\alpha}, \hat{\beta})$, we can estimate the mean and distributional sponsorship effects for the case of a dichotomous outcome variable, as described in Aavik et al., (2005). Let $\Delta = S_1 - S_0$, and $\Delta(x)$ be the expected value of Δ conditioned on $X = x$. Then, the sponsorship effect on the population (where the population is all the children within the appropriate age ranges

[10] I use Gauss-Hermite quadrature with 10 nodes to approximate the integral

for sponsorship), is defined as $ATE(x) = E[\Delta|X = x]$, and it can be estimated directly by:

$$
\begin{aligned}
ATE(x) &= Pr(Y_1 = 1|X = x) - Pr(Y_0 = 1|X = x), \\
&= F_{U_1}(x\hat{\beta}_1) - F_{U_0}(x\hat{\beta}_0), \\
&= \Phi\Big(\frac{x\hat{\beta}_1}{\sqrt{1+\hat{\alpha}_1^2}}\Big) - \Phi\Big(\frac{x\hat{\beta}_0}{\sqrt{1+\hat{\alpha}_0^2}}\Big).
\end{aligned}
$$

Also of interest is to know the sponsorship effect on the participants in the program, $ATT(x) = E[\Delta|X = x, S = 1]$, which can be estimated by:

$$
\begin{aligned}
ATT(x, z) &= Pr(Y_1 = 1|X = x, Z = z, S = 1) - Pr(Y_0 = 1|X = x, Z = z, S = 1), \\
&= \frac{1}{Pr(S = 1|X, Z)}(Pr(Y_1 = 1, S = 1|X, Z) - Pr(Y_0 = 1, S = 1|X, Z)), \\
&= \frac{1}{F_{U_S}(z\hat{\gamma})}(F_{U_1,U_S}(x\hat{\beta}_1, z\hat{\gamma}) - F_{U_0,U_S}(x\hat{\beta}_0, z\hat{\gamma})).
\end{aligned}
$$

Notice that given the distributional assumptions of the error structure, we can recover the covariates between the unobserved errors to the econometrician, where $Cov(U_S, U_1) = \alpha_1$, $Cov(U_S, U_0) = \alpha_0$, and $Cov(U_1, U_0) = \alpha_0\alpha_1$. Therefore, we can recover the joint distribution of (U_S, U_1, U_0). Furthermore, given the multidimensional normality assumption, we can recover the joint distribution of (U_S, U_1) and (U_S, U_0), which enables the estimation of the $ATT(x, z)$. Alternatively, using ε's distribution and integrating out θ, we can estimate the ATT by:

$$
\begin{aligned}
ATT(x, S = 1) = \frac{1}{E[\Phi(Z\hat{\beta}_S)/\sqrt{2}|X = x]} E_Z\Bigg(\int [\Phi(x\hat{\beta}_1 + \hat{\alpha}_1\theta) - \Phi(x\hat{\beta}_0 + \hat{\alpha}_0\theta)] \times \\
\Phi(Z\hat{\beta}_S + \theta)\phi(\theta)d\theta|X = x\Bigg).
\end{aligned}
$$

Finally, we can also estimate the marginal treatment effect, $MTE(x, u_S)$, which is a building block to estimate both $ATE(x)$ and $ATT(x)$ as shown by Heckman and Vytlacil (1999, 2005, 2007). The $MTE(x, u_S)$ is defined as $E[\Delta|X = x, U_S = u_S]$, which can be interpreted as the expected effect of sponsorship on the individuals with observed characteristics X, who are indifferent between studying higher education or not, given a value of z such that $z\gamma = u_S$. Notice that for small values of u_S, low levels of $z\gamma$ would be required for the individual to be selected into sponsorship. Similarly, if u_S is large, higher levels of $z\gamma$ would be required for the individual to be selected into sponsorship. In this sense, for low values of u_S, the $MTE(x, u_S)$ can be interpreted as the average effect of sponsorship for the most likely to be selected into the program. Similarly, for high values of u_S, the $MTE(x, u_S)$ would be the average effect of sponsorship for the least likely to be sponsored. The $MTE(x, u_S)$ can be estimated by:

$$
\begin{aligned}
MTE(x, u_S) &= Pr(Y_1 = 1|X = x, U_S = u_S) - Pr(Y_0 = 1|X = x, U_S = u_S), \\
&= Pr(U_1 \leq x\hat{\beta}_1|U_S = u_S) - Pr(U_0 \leq x\hat{\beta}_0|U_S = u_S).
\end{aligned}
$$

Again, since we have the bivariate distribution of (U_S, U_1) and of (U_S, U_0), and given the normality assumptions, we also have the distribution of U_1 and of U_0 conditioned on a value of U_S. Alternatively, we can estimate the marginal treatment effect by:

$$MTE(x, u_S) = \frac{\int [\Phi(x\hat{\beta}_1 + \hat{\alpha}_1\theta) - \Phi(x\hat{\beta}_0 + \hat{\alpha}_0\theta)]\phi(u_S + \theta)\phi(\theta)d\theta}{\phi(u_s)/\sqrt{2}}.$$

5 Results

Next, I report the estimates of the model. I first discuss the estimation of the selection and outcome equation, and then present the estimation of the mean sponsorship effects. Finally, I further detail the heterogeneity in the impact of sponsorship by presenting the marginal sponsorship effect for different values of u_S.

In the first column of each model of Table 3, we observe the coefficients of the selection equation. The results for model 1 correspond to the estimation of the model without the believed returns of higher education ρ_{HE} in the outcome equation, whereas model 2 does include ρ_{HE}. Consistent with CI's selection procedure, younger cohorts have a higher probability of being selected than older cohorts. Also, being protestant is positively correlated with selection, and a higher asset index (greater wealth as measured by household goods) is negatively correlated with selection to the program. In the second column of each model, I report the marginal effect of each covariate defined as $E_Z[\frac{\partial Pr(S=1|Z=z)}{\partial z_k}]$, which is estimated using the analytical derivative averaged over the unconditional distribution of Z. Younger cohorts are around 25 percentage points more likely to be selected into the program, and an increase of one standard deviation in the asset index is related to a decrease of approximately three to four percentage points of being selected into the program.

The estimates for the outcome equation are presented in Table 4. As mentioned before, the difference between the two specifications is the inclusion of ρ_{HE} in model 2. Also, the lower sample in model 2 reflects the fact that some children could not interpret the probability questions[11]. First to notice is that the coefficients are fairly imprecisely estimated. The standard errors, estimated by bootstrap, are large enough for most of the coefficients to be insignificant. The results suggest that a larger data set may be needed. Given the imprecision of the estimates, these results can be taken as suggestive rather than conclusive. Nevertheless, the signs of the coefficients have the expected direction which I proceed to describe. Furthermore, I can still learn about the correlation between sponsorship and selection to the program, a key result to test the CI's targeting of sponsored children. Under both specifications, the coefficients for the sponsored and the non-sponsored are

[11] I have also estimated the model assuming that income follows a uniform distribution, which avoids the use of the probability questions to estimate the subjective beliefs on the returns to higher education. The results are similar and are available upon request.

Table 3: Selection equation

	Model 1		Model 2	
	Coeff.	Mg. Effect	Coeff.	Mg. Effect
	(1)	(2)	(1)	(2)
Factor	1		1	
Age 6	1.190***	0.215***	1.694***	0.257***
	(0.323)	(0.052)	(0.554)	(0.058)
Age 7	1.63***	0.210***	1.846***	0.285***
	(0.344)	(0.054)	(0.406)	(0.048)
Age 8	1.434***	0.259***	1.673***	0.271***
	(0.277)	(0.043)	(0.324)	(0.036)
Protestant	1.309***	0.236***	1.923***	0.338***
	(0.251)	(0.044)	(0.329)	(0.045)
Asset Index	−0.165**	−0.029**	−0.27***	−0.043**
	(0.083)	(0.014)	(0.152)	(0.02)
Treated site	3.313	0.599***	3.149	0.432***
	(2.891)	(0.027)	(3.529)	(0.047)
N	403	403	271	271

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

reported in columns one and three respectively, along with their marginal effects in columns two and four.

Interestingly, in Table 4, the program *Prospera* is positively correlated with aspirating to a higher education degree, both for the sponsored and non-sponsored, which may signal positive benefits of expanding the income sponsorship transfers. Males have a lower revealed intended choice to acquire higher education both for the sponsored and non-sponsored. The asset index is significant and positive only for the non-sponsored, with a marginal effect of 6 to 33 percentage points. Parental education, as expected, is consistently positive, with a marginal effect around 2.7 to 5 percentage points per year of education for the sponsored, and 2.3 percent for the non-sponsored.

Finally, although the children's subjective expectations of future income are realistic even though heterogeneous, at least at the ages of 12 to 15, they do not seem to take these beliefs into consideration when thinking about their aspiration to acquire a higher education degree. At these young ages, there might be other factors, both internal (e.g., lack of grit, self-esteem, hope) and external (e.g., income constraints) that may be impacting the children's aspirations. Also, it might be that for the rural context studied, with low levels of education, the aspiration to acquire

Table 4: Output equation. Output = dummy equal to one if the intended choice of schooling is higher education.

	Model1				Model 2			
	Sponsored	Marginal effect	Non-Sponsored	Marginal effect	Sponsored	Marginal effect	Non-Sponsored	Marginal effect
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
α	0.025		-0.492		-0.077		-0.977	
	(0.459)		(0.515)		(0.934)		(0.903)	
Prospera	0.173	0.057	0.255	0.076	0.326	0.112	0.021	0.005
	(0.404)	(0.108)	(0.333)	(0.091)	(0.632)	(0.154)	(0.64)	(0.127)
Male	-0.131	-0.043	-0.394	-0.119^{**}	-0.236	-0.078	-0.144	-0.035
	(0.253)	(0.074)	(0.251)	(0.055)	(0.403)	(0.097)	(0.451)	(0.08)
Asset Index	0.049	0.016	0.111	0.336^{***}	-0.033	-0.011	0.25	0.06^{**}
	(0.087)	(0.024)	(0.103)	(0.022)	(0.133)	(0.033)	(0.229)	(0.03)
Parent Educ	0.082^{*}	0.027^{**}	0.077	0.023^{**}	0.138^{*}	0.05^{***}	0.087	0.024
	(0.045)	(0.013)	(0.051)	(0.010)	(0.073)	(0.017)	(0.083)	(0.015)
Distance	-0.002	-0.006	0.001	0.0004	-0.001	0	0.003	0.001
	(0.002)	(0.0008)	(0.003)	(0.0008)	(0.004)	(0.001)	(0.007)	(0.001)
ρ_{HE}					-0.343	-0.113	0.065	0.016
					(0.474)	(0.072)	(0.479)	(0.069)
$E(ATE(x))$	0.016				-0.008			
$V(E(ATE(x)))$	(0.083)				(0.009)			
$E(ATT(x))$	0.170				0.204			
$V(E(ATT(x)))$	(0.183)				(0.180)			
N	403	403	403	403	271	271	271	271

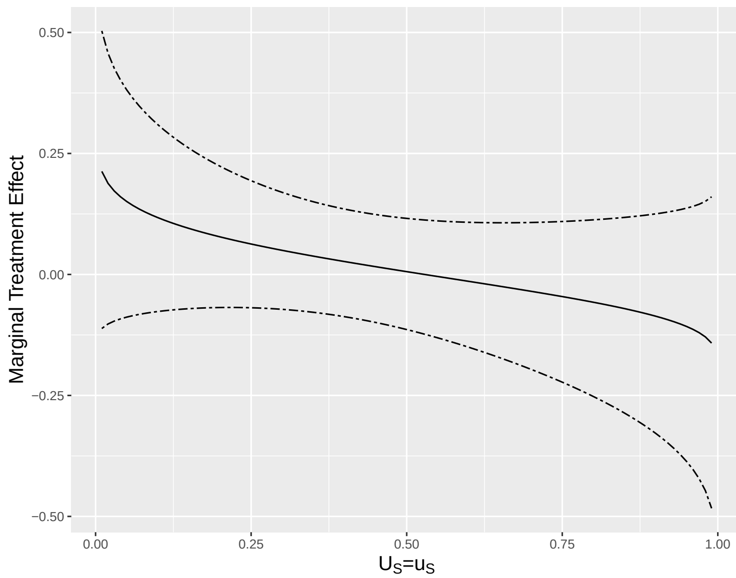
Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

a higher education degree might be too high, such that even though the children's beliefs on the returns to schooling are realistic, they might think it is not attainable. In either case, a focus on encouraging more short-term attainable goals could be valuable.

Although imprecisely estimated, due to the large standard errors, we have that the sponsorship effect on the population is effectively null, but on the sponsored individuals is about 17 to 20 percentage points. Nevertheless, both of these effects are not significant at the standard levels. The difference between the average sponsorship effect and the sponsorship on the participants can be better explained by the marginal treatment effect (MTE). In Figure 2 we plot the MTE, with a 95 percent interval, for different values of U_S for model 1. The results for model 2 are similar and can be found in the Appendix in Figure 6. The effect of sponsorship is positively correlated with selection to the program, as the individuals with lower u_S have a higher sponsorship effect. As shown by Heckman and Vytlacil (2007), we can use the MTE as a building block for the ATE and

ATT, where the ATE is an integrated version of the MTE using the appropriate weights. Likewise, we can also recover the ATT with higher weights for low levels of u_S, which is consistent with the results obtained.

Figure 2: Marginal Treatment Effect - Model 1



Although the treatment parameters are not significant, the sponsorship effect on the participants is consistent with the results observed by Wydick et al., (2013), who find an impact of CI on completed years of schooling in the range of 1.03 to 1.46 years. If the intended choices would match actual behavior, an increase in 20 percentage points on aspirations would translate into an increase of approximately 8 months of schooling. An interpretation of this result is that even smaller increments in the educational aspirations of children may be valuable, given that aspirations tend to build on themselves.

5.1 Discussion

On a methodological note, children may take into account unobservable factors, such as a self-sense of ability, when answering the questions about their believed future income. In that case, the elicited returns to schooling would be correlated with the factor and the results would be biased. Notice though, that if the believed returns to schooling are correlated with the factor, we can use this variable as a measurement within a measurement system as in Cunha and Heckman (2008). The believed returns are observed for all individuals and do not suffer from a selection problem. Its inclusion in a measurement equation allows us to have three additional covariates, which identify the model through the covariate of the residuals.

A difficulty of estimating this model through the measurement system is that we would need the estimation of the residuals (U_S, U_1, U_0). The estimation of U_S can be done by using the quantiles of the probit model for the selection equation, and the estimation of U_1 and U_0 is straightforward when we have a continuous outcome. Nevertheless, for the case of binary outcomes, we have to account for the nonlinearity of the model, and the implementation of a measurement system is not trivial. If our outcome variable would have been continuous, such as the acquired level of education, a measurement system using the beliefs as a measurement would be feasible. Nevertheless, when studying the aspiration to acquire further studies than high-school, we consider it appropriate to use a discrete outcome as children aspirate to a predetermined level.

6 Conclusions

In this paper we estimate the impact of the international child sponsorship program, *Compassion International* (CI), on the aspiration of rural children aged 12 to 15, in Mexico, to acquire a higher education degree. We add structure to the estimation of the sponsorship effect to account for the selection procedure of the sponsored students. The added structure, following Aakvik et al., (2005), allows us to study how the selection to the program correlates with the treatment effect. The standard errors of the outcome coefficients are large, so we take these results as suggestive rather than conclusive. We observe an average treatment effect on the treated of 17 to 20 percentage points, although these estimates are not statistically significant at the usual levels. We further estimate the marginal treatment effect for different values of the selection error term. The results show that selection to sponsorship is positively correlated with the treatment effect. In other words, the sponsorship is higher for the children that are most likely to be selected for sponsorship, which is reassuring.

It is important to interpret these results within the broader context of studies about CI. In early work, Wydick et al., (2013) study CI's impact on realized outcomes after the sponsorship ends, and find a positive effect on schooling of 1.03 to 1.46 years. Furthermore, work by Glewwe et al., (2017) and Ross et al., (2020), show positive effects of CI on children while being sponsored in measures of hope, happiness, self-efficacy, optimism, and on an aspirations index that uses, among one of its inputs, a continuous variable of years of schooling. In this study, we estimate the sponsorship effect on rural children in Mexico, on a high aspirational target, the intended choice of acquiring a higher education degree. I find that the results, although positive and consistent with the previous studies, are not statistically significant. From the cumulative studies, CI has a positive effect on the socio-emotional development of children, especially when we look at psychological indexes. Nevertheless, for the case of rural children in Mexico, that positive effect diminishes when we look at a high aspirational target, as acquiring a higher education degree. Consistent with Genicot and

Ray (2017), and Lybbert and Wydick (2018), a focus on encouraging more short-term attainable goals, and continuous support, as CI's approach, may be preferred over setting overly high goals.

Finally, we also estimate and study the children's subjective beliefs of future income. We document that rural children's beliefs, although heterogeneous, do not divert significantly from census data. This may be because within a rural context in Mexico, children start working from an early age. Despite having realistic expectations, we find two patterns. First, a large gender gap in expectations even at the ages of 12 to 15, and the fact that, at least at these ages, their subjective beliefs of future income do not seem to impact significantly their aspiration to acquire a higher educational degree. These results do not imply that the beliefs of future income are not important, but that for young children in rural contexts, other factors are driving their aspirations.

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7 Appendix

Table 5: Summary statistics: sponsored vs non-sponsored

	Site with CI			Site without CI	
	Sponsored	Sibling of sponsored	Non-sponsored in non-sponsored HH	Non-sponsored in non-sponsored HH	Mean all
Higher education[1]	0.712	0.656	0.809	0.688	0.730
	(0.454)	(0.483)	(0.395)	(0.466)	(0.445)
University[1]	0.571	0.563	0.713	0.613	0.620
	(0.497)	(0.504)	(0.454)	(0.490)	(0.486)
Age	13.006	14.156	13.530	13.559	13.375
	(1.003)	(0.847)	(1.111)	(1.127)	(1.105)
Male	0.429	0.594	0.470	0.495	0.469
	(0.497)	(0.499)	(0.501)	(0.503)	(0.500)
Birth order	2.441	2.031	2.800	2.367	2.495
	(1.635)	(1.062)	(2.023)	(1.686)	(1.740)
Num. siblings	3.945	4.844	3.913	3.596	3.930
	(2.088)	(1.953)	(2.088)	(1.730)	(2.019)
Protestant	0.730	0.563	0.365	0.269	0.506
	(0.445)	(0.504)	(0.484)	(0.446)	(0.501)
Prospera[2]	0.871	0.906	0.878	0.839	0.868
	(0.336)	(0.296)	(0.328)	(0.370)	(0.338)
Education father	7.000	6.633	6.745	6.562	6.797
	(3.006)	(3.499)	(3.336)	(3.316)	(3.207)
Education mother	6.321	5.500	6.800	6.742	6.490
	(3.283)	(3.282)	(2.832)	(3.247)	(3.161)
Asset index	-0.216	-0.229	0.378	0.239	0.057
	(1.516)	(2.345)	(1.313)	(1.511)	(1.561)
N	163	32	115	93	403

Standard deviations in parenthesis.

[1] Denotes that the child expect to achieve a higher education degree, or a university degree respectively.

[2] Dummy equal to 1 if the child's household participates in *Prospera.*

Table 6: Comparisons by groups

	(Sponsored) vs (Non-sponsored sponsored sites)	(Sponsored) vs (Non-sponsored in non-sponsored sites)	(Non-sponsored in non-sponsored site) vs (Non-sponsored HH in in sponsored site)
	t-test	t-test	t-test
Higher education[1]	-0.097*	0.023	-0.128**
	(0.052)	(0.059)	(0.061)
University[1]	-0.142**	-0.042	-0.107
	(0.058)	(0.064)	(0.066)
Age	-0.524***	-0.553***	0.023
	(0.124)	(0.131)	(0.147)
Male	-0.040	-0.065	0.020
	(0.059)	(0.065)	(0.068)
Birth order	-0.359	0.074	-0.426
	(0.274)	(0.247)	(0.316)
Num. siblings	0.032	0.349	-0.280
	(0.312)	(0.288)	(0.337)
Protestant	0.365***	0.461***	-0.089
	(0.062)	(0.061)	(0.068)
Prospera[2]	-0.007	0.032	-0.038
	(0.044)	(0.051)	(0.055)
Education father	0.255	0.438	-0.223
	(0.449)	(0.487)	(0.547)
Education mother	-0.479	-0.421	-0.130
	(0.409)	(0.464)	(0.478)
Asset index	-0.595***	-0.456**	-0.169
	(0.189)	(0.228)	(0.232)
N	278	256	209

Standard errors in parenthesis.

*** p<0.01, ** p<0.05, * p<0.1

[1] Denotes that the child expects to achieve a higher education degree, or a university degree, respectively.

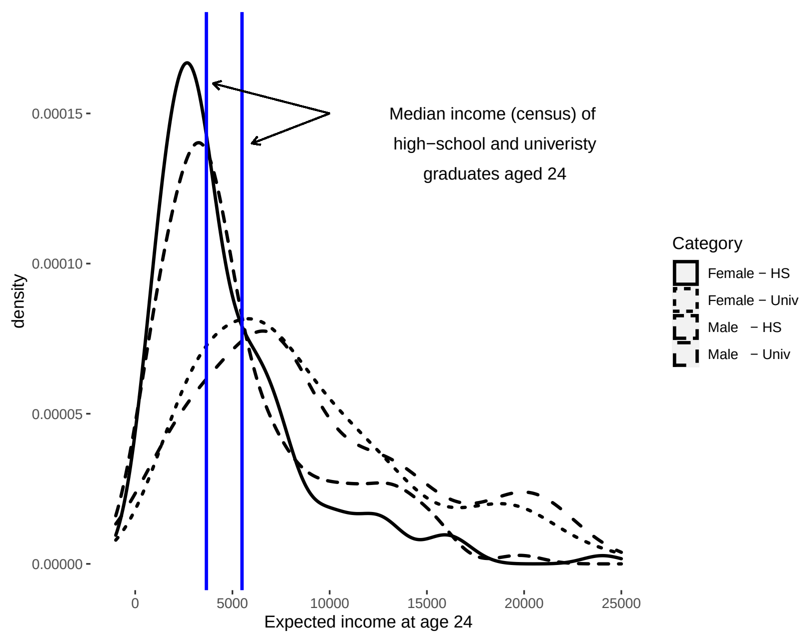
[2] Dummy equal to 1 if the child's household participates in *Prospera.*

Table 7: Comparisons by site

	Mean all (S.D.)	Sponsored site (S.D.)	Non-sponsored site (S.D.)	t-test (S.E.)
Higher education	0.730	0.744	0.681	0.063
	(0.445)	(0.437)	(0.469)	(0.054)
University	0.620	0.625	0.606	0.018
	(0.486)	(0.485)	(0.491)	(0.058)
Age	13.375	13.320	13.553	-0.233*
	(1.105)	(1.095)	(1.123)	(0.121)
Male	0.469	0.463	0.489	-0.027
	(0.500)	(0.499)	(0.503)	(0.059)
Birth order	2.495	2.531	2.374	0.157
	(1.740)	(1.759)	(1.678)	(0.237)
Num. siblings	3.930	4.016	3.633	0.383
	(2.019)	(2.083)	(1.757)	(0.266)
Protestant	0.506	0.576	0.277	0.299***
	(0.501)	(0.495)	(0.450)	(0.057)
Prospera	0.868	0.877	0.840	0.037
	(0.338)	(0.329)	(0.368)	(0.047)
Education father	6.797	6.881	6.522	0.359
	(3.207)	(3.174)	(3.319)	(0.457)
Education mother	6.490	6.435	6.670	-0.235
	(3.161)	(3.120)	(3.303)	(0.424)
Asset index	0.057	0.011	0.209	-0.198
	(1.561)	(1.569)	(1.531)	(0.216)
N	403	309	94	403

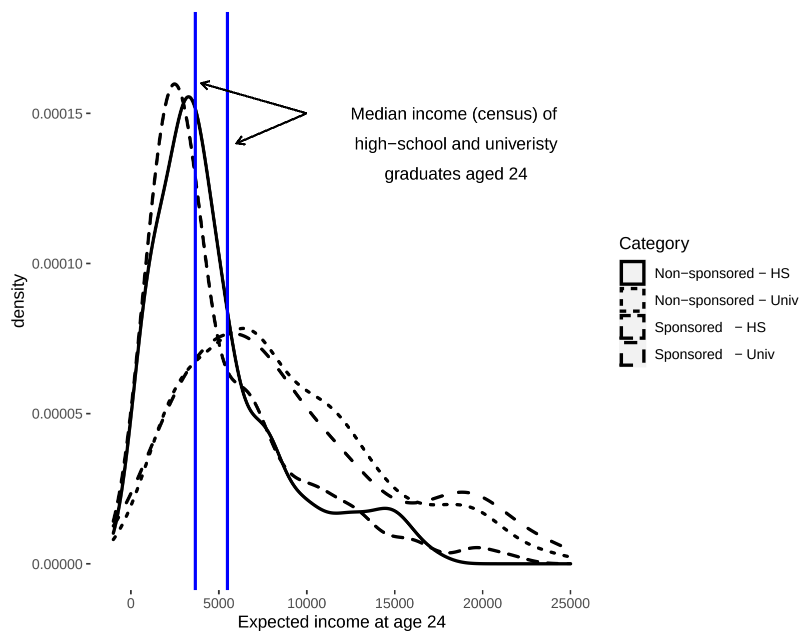
*** p<0.01, ** p<0.05, * p<0.1

Figure 3: Expected income distribution for high-school and university by gender: Triangular distribution of income



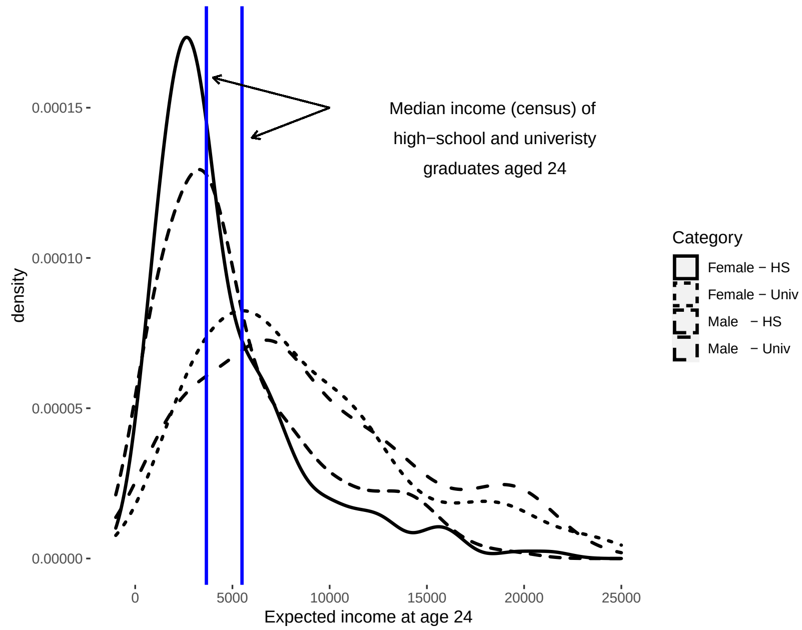
Note: the estimations assumes a triangular distribution of income.

Figure 4: Expected income distribution for high-school and university by sponsorship status: Uniform distribution of income.



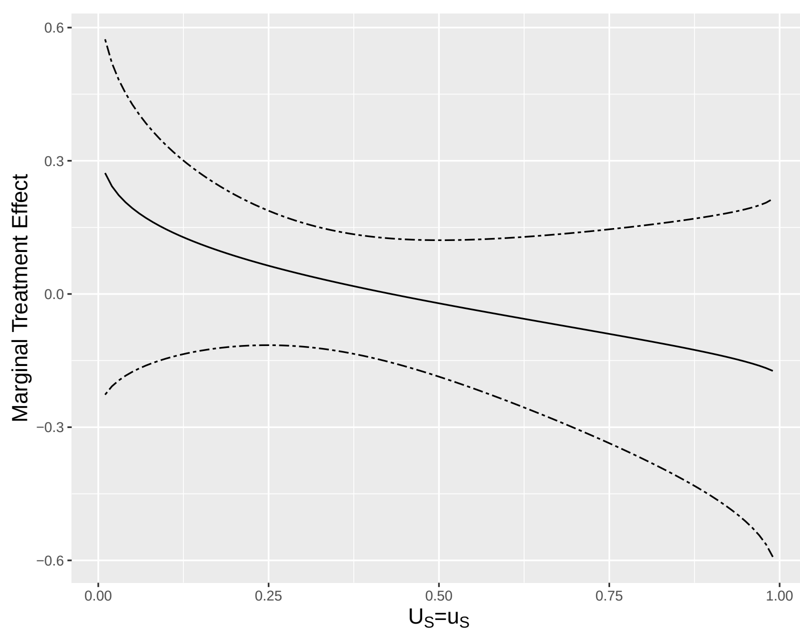
Note: the estimations assumes a uniform distribution of income.

Figure 5: Expected income distribution for high-school and university by gender: Uniform distribution of income.



Note: the estimations assumes a uniform distribution of income.

Figure 6: Marginal treatment effect, Model 2:
Triangular income distribution.



Note: U_S denote the error of the selection equeation.

Table 8: Expected income vs census data data at age 24 (mean of data)

	High-school			Technical school			University		
	Male	Female	Total	Male	Female	Total	Male	Female	Total
Census									
Oaxaca less than	4829.2	3898.4	4484.8	5693.3	4646.7	5102.9	6446.6	6162.8	6291.9
50,000 residents	(4293.9)	(2577.1)	(3777.6)	(3296.6)	(2939.9)	(3123.7)	(3661.4)	(3058.3)	(3348.0)
Oaxaca more than	5434.2	4313.6	4971.7	7933.1	4485.5	5470.5	5680.2	6183.7	5948
50,000 residents	(4359.6)	(1691.5)	(3549.4)	(5394)	(2008.4)	(3220)	(3052.2)	(3231.6)	(3151.8)
Chiapas less than	3681	3189.4	3561.5	4940.9	3971.4	4545.9	5770.6	5506.5	5650.9
50,000 residents	(2749.4)	(2300)	(2655)	(4208.7)	(2646.5)	(3656.1)	(3504.8)	(3042)	(3304.2)
Chiapas more than	4685.3	3867.2	4374	7847.8	5307.6	6718.8	8356.8	6567.6	7496.2
50,000 residents	(2444.1)	(2397.4)	(2456.6)	(4876.8)	(3806.1)	(4372.2)	(27981.3)	(4658.4)	(20422.7)
Survey									
Oaxaca Sponsored	6683.9	4026.6	5306	9476.2	5766.3	7552.6	13909.4	7533.9	10603.6
	(4550.5)	(2974.5)	(3976.4)	(5557.4)	(4583.2)	(5322.2)	(8135.9)	(5865.4)	(7634.8)
Oaxaca Non-Sponsored	5966.5	10195.3	8080.9	10719.4	12033.4	11376.4	15387.3	15713.8	15550.6
	(4992.9)	(18417.2)	(13414.7)	(11393.9)	(20065.9)	(16025.6)	(16475.7)	(25780.8)	(21230.6)
Chiapas Sponsored	6422.2	5380.3	5786.9	8761.6	7391	7925.9	12944.5	12363.2	12590.1
	(8553.6)	(5440.1)	(6794.5)	(10896.8)	(6503.7)	(8454.8)	(16637.1)	(15539.1)	(15877.2)
Chiapas Non-Sponsored	5371.7	4979.9	5167	8772.5	7332.4	8020.2	15164.5	12318.9	13678
	(4554.8)	(3861.7)	(4195.5)	(8197.8)	(5905)	(7102.4)	(16785.5)	(10924.4)	(14050.3)
Attanasio and Kaufman (2014) - averages	3525.5	2509.3					6110.6	4806.8	

Note: Standard deviations in parenthesis.