

Increasing Educational Attainment in Guatemala: Evaluating the Impacts of a Comprehensive Conditional Transfer Program

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Using duration analysis, we estimate that by providing comprehensive services and support to poor families in Guatemala conditional on the enrollment of at least one child in school, Common Hope is able to bring about a 23% increase in expected attainment for children living in affiliate households. The magnitude of this effect is large in comparison to other conditional targeted transfer programs, such as PROGRESA, indicating that the comprehensive nature of the benefits provided by Common Hope is of high value, or embodies complementarities to education resulting in increasing returns.

In the vast landscape of international NGO's, Common Hope, in Antigua Guatemala, stands as an interesting example of long-term, large scale program with a coherent philosophy and a generous private donor base. The program has a variety of diverse goals, but increasing the educational attainment of affiliated children and giving them the tools to break out of intergenerational cycles of poverty have always been the central focus of their efforts. This primary goal, and the individual conditionality which is used as a means for achieving it, makes Common Hope an interesting case study in relation to the increasingly popular national scale conditional targeted transfer (CTT) programs across Latin America.¹ Highly touted as an efficient, effective means to induce investments in human capital, CTT programs focused on education have been tested and evaluated using randomized experiments in Mexico, Nicaragua, and Honduras lasting 2-3 years. Common Hope has been active in Guatemala for over ten years, allowing for the unique opportunity to study the long term impacts of program affiliation.

¹ These programs are sometimes referred to as "Conditional Cash Transfers" (CCT) in other papers. Here we have chosen to use the more general "targeted transfer" because we discuss both programs that employ cash transfers (PROGRESA, etc.) and programs that use grain (FFE) and services (Common Hope) as the benefit.

Common Hope is not a strict cash transfer program, but the same logic of a conditional payment is employed; families are offered an array of valuable services if they enroll a child in primary school. The comparable logic, combined with a longer time span that children benefit from “treatment” under the umbrella of Common Hope, led to the conception of a survey of beneficiaries which could quantify the impacts of the program. By gathering information on the educational history of long term affiliates as well as recall data on past employment and housing we were able to construct a “quasi-experimental” design, roughly similar to the baseline/post program panels constructed in the evaluation of the larger scale CTT programs. This evaluation will lend insight into both the internal logic and incentive structures driving educational decision making of families affiliated with Common Hope. Thinking about the design of Common Hope in the context of the lessons learned from the other CTT programs will suggest modifications to the existing program that could improve both outcomes and efficiency. Additionally this evaluation will allow us to think about ways that traditional CTT programs might be modified or improved based on a more comprehensive benefit structure. Specifically, the nature of in-kind transfers of services and goods rather than cash may allow more efficient targeting of benefits as well as a more effective means for responding to shocks. The flexibility of the Common Hope benefit structure allows the program to act as an insurance mechanism against risk; it is not only an incentive to continue schooling and an augmentation to income, but also a safety net against shocks detrimental to the livelihoods of the poor.

The first section will begin with a discussion of programs that approach the issue from the supply side, and those that use a demand stimulus approach. A description of the design and policies of Common Hope, a targeted poverty alleviation program in Antigua, Guatemala, follows. Next, we briefly discuss the theoretical and empirical basis for modeling education. The heart of the analysis consists of empirically quantifying the impact of Common Hope on the education decisions of families by estimating a duration model. Using the results of the duration regression, we predict the expected value of attainment for program participants. Duration analysis has not been widely utilized in education research, although it is well suited to data on schooling, and the discreet data techniques employed in this analysis build on the existing methodology for impact

evaluation studies. Finally, we discuss conclusions that can be drawn from the analysis of Common Hope, as well as potential modifications to the Common Hope program that might arise from the findings of this evaluation. Additionally, we draw on the unique design of the Common Hope program in discussing the future of conditional transfers in Latin America and across the developing world, with an eye towards potential improvements in efficiency and targeting of benefits.

Promoting Education through Supply and Demand

The traditional approach to promoting enrollment has been to invest in the supply of education by building schools and training teachers. This supply side approach depends on providing access to schools for children who live in remote, rural areas, and on increasing the expected returns by improving both facilities and the quality of teaching. One major drawback to the supply side approach is that it is difficult to target the poorest of the poor. Building a school in a rural area will surely target that geographical region; however, it does not guarantee that the poorest households will choose to enroll their children. Each household is still left to make a decision based on the current costs of schooling weighed against the future benefits. It is still the poorest of the poor who are less likely to enroll. Clemens (2004) states that “with limited demand, governments can lead their young people to the fountain of education, but cannot make them drink,”. Experience has proved him right.

Clemens (2004) also reminds us that during the past seven decades the developed world has come together to reaffirm a commitment to universal primary education no less than eighteen separate times. He proposes that given the historical homogeneity in the growth of enrollment rates, universal primary education on a short time horizon is an unreasonable goal. However, a reorientation from supply to demand side education policies might render universal primary education bypasses the income-credit constraint and makes schooling a viable and even profitable option for the poor.

Recent development initiatives, pioneered in cooperation with the International Food Policy Research Institute (IFPRI), suggest a solution that attacks the problem of low enrollments primarily by lowering the effective price, rather than increasing the quantity and quality of supply. Families (normally mothers) receive a monthly payment

conditional on the enrollment of one or more children in school. Each program varies slightly, some pay per child and others per family. Some cover only primary school and others continue into secondary. Most contain a supply side component to deal with the crowding caused by increased enrollment. Each program has one commonality; transfers are made conditional upon the enrollment and attendance of children in schools. The money is meant to offset the direct costs of education and the opportunity costs of forgone wages. Unlike strict supply side interventions, these programs can be much more directly targeted to the poor by offering payments only to households with certain characteristics, or households in certain geographic areas. Although there are significant challenges in designing an effective and efficient targeting scheme, this type of intervention has the potential to be much more pro-poor than the supply side approach.²

Common Hope, the Guatemalan NGO which is the focus of the analysis in this paper, is designed around a similar demand side incentive structure. Affiliation with the program and receipt of benefits are conditioned upon school enrollment of at least one child in the household. Additionally, Common Hope helps to build extra classrooms in crowded schools, provides special education services, and conducts teacher training. This program is comparable to the large scale cash transfer programs based on the logic of the design and conditionality.

During the past decade, demand side Conditional Targeted Transfer programs (CTTs) have been initiated in Mexico (PROGRESA), Nicaragua (RPS), Honduras (PRAF), and Bangladesh (FFE). Extensive evaluations exist, chronicling their impacts on education, poverty, child labor, and the cost effectiveness of the outcomes. A brief review of educational impacts follows.³

Raymond and Sadoulet (2003) found that overall impact of the cash payments through PROGRESA, which constituted 21-40% of household income, was an increase of average attainment from 6.8 years in the control group to 7.4 years in the treatment group, a +9% change in expected attainment. This is consistent with the impacts cited in other studies of PROGRESA (Schultz, 2001; Behrman et al, 2001). They also find

² Ravallion (2003); Conning and Kevane(2000); Gallasso and Ravallion(2001); Coady(2001); Coady et al. (2004) write explicitly about the challenges and tradeoffs involved in targeting anti-poverty programs.

³ A more comprehensive literature review on program design, targeting, evaluation and outcomes of all major educational transfer programs can be found in Morely and Coady (2003) or Rawlings and Rubio (2003).

heterogeneity in the impacts based on household characteristics. The larger gains for poorer children actually *equalized* schooling levels across levels of wealth within the program, which is especially important in light of the constraints to increasing enrollments imposed by low incomes and imperfect financial markets. Children who lived more than 3km from the school gained significantly, and far surpassed the average education for the control group, suggesting that to some extent demand side grants can address the supply issue in a much more efficient manner than school construction.

Analysis of RPS utilized the randomized assignment of the treatment and control communities and baseline data collection to estimate difference-in-difference impacts over the two year treatment period. Using this technique, researchers found a 17.7% increase in enrollment, on average, across the 7-13 year old sample. There was also a significant impact on attendance rates, with 23% more attendance among the treatment group (Maluccio and Flores 2004). In the case of RPS, the

The impact of PRAF was much more muted than the other programs. Difference in difference analysis yields only a 2% increase in enrollment over the control group. However, factors exogenous to the program induced a 10% increase in the enrollment of 6-12 year olds within the control, representing a significant change in schooling patterns during this period in Honduras. Again, there was evidence of a progressive impact based on income, meaning that poor households gained relative to more wealthy households (Glewwe and Olinto, 2004).

Total enrollment in FFE schools increased by 44% for girls and 28% for boys (35% on average); in the same period the national enrollment increase was 2.5%. Although this study did not benefit from randomized experimental design with a comparable control group, it is relevant to compare the FFE schools to schools outside the program they are not significantly different from non-FFE schools. The magnitude of the impact is so large it hardly matters; it is clear that FFE had huge effects on enrollment. There was additional evidence for an impact on attendance and dropout rates; attendance rates in FFE schools were 70% as compared to 58% in other school, and the dropout rate was 6% rather than 15%.

The diversity among program outcomes can be attributed to different sized transfer payments, but some of the variety is also a consequence of the varied initial

educational and economic conditions faced in each country. In Bangladesh and Nicaragua, low household incomes and initially low attainment mean that smaller transfers have a larger impact than in Mexico, where household incomes are relatively higher and primary enrollment is nearly universal. The programs in Nicaragua and Honduras are targeted to first through fourth grades due to low levels of primary schooling in those countries, but in Mexico the payments extended to ninth grade. Comparing accomplishments across countries is made difficult by the varied initial conditions, but in every program for which there is evidence, demand side programs have yielded statistically significant increase in average educational attainment or enrollment within the beneficiary group.

How do the costs of achieving increased enrollment from a demand side approach compare to a strict supply side approach? Coady and Parker (2004) examine the effects of PROGRESA at the secondary school level and compare the cost effectiveness of demand and supply side approaches. By estimating the impact of distance from school on enrollment, they are able to calculate the educational impact of building schools (decreasing distance to school), and the cost of achieving this impact. For comparison purposes, they convert this to a cost-per-extra-year metric (or cost effective ratio- CER). On the demand side they calculate the total cost of the schooling subsidies, and convert this to a CER measurement. The highest estimated CER on the demand side is \$12,600. The lowest estimate of the CER for supply expansion is \$103,600.⁴ The difference is striking. Even though these figures are rough estimates that cannot fully capture all of the costs involved, it is clear that building schools is a vastly more expensive way to achieve increases in attainment than demand stimulus programs. However, if enrollments increase, it will be vital to expand capacity in order to accommodate the increased demand.

With the backdrop of the successful CTT programs across Latin America and a more thorough understanding of the potential for change through demand side intervention, we now move to the description and evaluation of Common Hope, a targeted demand side program that operates on the basis of conditionality. The

⁴ Different specifications yield a CER exceeding \$350,000 on the supply side, while the most conservative demand side estimate is \$6,900.

“transfers” in the case of Common Hope are of valuable services rather than cash, and this distinction presents a variety of extra challenges, as well as potentially important innovations and lessons for the larger scale programs. Additionally, the Common Hope provides a unique opportunity of evaluating the impacts of long term exposure to demand side conditionality, an opportunity not afforded by the evaluations of the experimental CTT programs.

Description of Common Hope

Since its inception as the Godchild Project in 1986, Common Hope has always focused on direct sponsorship of poor children whose families receive the benefits of a variety of services and support offered by Common Hope conditional on educational participation of the sponsored child. Over the years the array of comprehensive services has expanded and evolved to meet the changing needs of families and communities. The scope of the project has also expanded, and now serves 15 villages within a 20 mile radius of the north side of Antigua. In 1993 a large facility was constructed about a mile outside of Antigua to house the clinic, educational services, staff, volunteers and work teams from the US.

Common Hope’s services are focused in the areas of education, health, housing, emergency assistance and family development. The education component consists of paying some or all of the costs of schooling for affiliated children, as well as providing mandatory tutoring for all students beyond primary school, optional summer school, extracurricular interest groups, and day care for younger children. Additionally, adult education classes in both literacy and vocational areas are open to all members of the affiliated families.

Health care is provided both through a Common Hope clinic on the grounds of the facility, as well as through local hospitals and private clinics when needed. The Common Hope clinic has full time doctors and dentists, the ability to treat and prescribe medicine for many illnesses and injuries, and equipment to conduct laboratory testing and x-rays. Other health programs include oral hygiene, nutrition education, prenatal care, immunizations, and vision care. If an illness or injury is too serious to be treated by the doctors on site, Common Hope will usually pay for care off site.

The main focus of the housing program is to improve the materials of home construction. By volunteering at the main facility, families earn service hours which can be used towards the purchase of new housing materials like roofing tin, moveable cement floor tiles and cinder blocks or “fibrolit” (a material between drywall and plywood) for the walls. It is also possible to earn a woodstove with a chimney for venting smoke from cook fires, or a moveable latrine. As with many aspects of the Common Hope program, the housing assistance is driven by the philosophy that the best development work is based not on providing for people, but assisting and empowering them to provide for themselves. The involvement of the affiliated family is seen as instrumental to the success of the housing program, and the whole Common Hope project.

The emergency assistance component of Common Hope acts as a safety net to ensure that basic needs are met in affiliate families. Supplemental food is provided if households experience shocks that threaten food security or if they live on the edge of subsistence. Clothing and shoes are also provided, especially for children in school, if households cannot afford them.

Family development at Common Hope is centered on the relationship between the social worker and the affiliate family. The social worker keeps track of the progress of the children in school, the working situation of the parents, and the general living environment. For families that have the need, there are also couples counseling services, support groups like AA, teen groups, and a grandmother’s group.

We estimate the value of the services and benefits to be \$75 a month, per family⁵, although the value of benefits varies significantly across families. This translates to about 37% of household income, based on the current mean income among affiliate families. Recall that for PROGRESA benefits constituted 20-40% of household income, depending on the age and number of children in school. It seems that the level of support through Common Hope is, on average, similar to the level of support in the PROGRESA program, but larger than other programs like RPS that are based on much smaller transfer sizes.

⁵ According to commonhope.org, 84% of funds go directly into programs, with the remaining 16% devoted to fundraising and management. According to director Joh Huebsch, Common Hope spends a total on about \$90 per child, which works out to \$75.60 going directly into the benefits.

Families gain affiliation with the program by applying directly and going through a review with a social worker. The organization has developed a framework for making affiliation decision, which is used by the social workers to assess the family situation based on the makeup of the household, the number of children, the means the family has of supporting itself, the domestic situation, the living situation, and any extenuating circumstances. When a family is granted affiliation they sit down with their social worker to discuss the programs in which they are interested in participating, and the social worker helps them map out a plan for their affiliation.

Sponsored children are considered “full affiliates” through primary school, during which time the entire family of the affiliated child has access to the full range of services provided by Common Hope. Once a child progresses past primary school, they become affiliated with what is called a “beca”, or scholarship. At this stage the organization still covers most of the direct costs of education and provides tutoring services and health care for the affiliated child, but the benefits for the rest of the family are no longer guaranteed. In some cases the benefits of full affiliation are extended past primary school. Households often have more than one affiliated child, in which case they continue to receive the full benefits of affiliation as long as at least one affiliate is in primary school.

The affiliation policies complicate how we think about conditionality because of the uncertainty involved in the termination of benefits after primary school and the possibility of multiple affiliates. The full benefits of the program at the family level are essentially conditioned on the grade level and enrollment of the youngest affiliate. Other affiliates receive schooling related costs in return for enrollment, but the conditional value of these benefits is much smaller than the value of the full affiliation. Throughout this paper we refer to any child who is currently or was in the past directly affiliated with the program as an “affiliate”, keeping in mind that the conditional value of affiliation depends on the grade level of each child, and the affiliation status of his or her siblings.

Throughout this paper we use the term “treatment” to refer to any household who is or was receiving the benefits of affiliation with Common Hope, even if those benefits consist only of the secondary school scholarship. Any household who has ever had a child directly sponsored by Common Hope falls into the treatment group, and all

members of those households, regardless of age or direct sponsorship are considered part of the “treatment” group.

The overall logic of the large scale CTT programs and the more comprehensive Common Hope program are nearly identical. In both cases, families who face high opportunity costs of education for their children receive benefits with economic value in return for enrollment. The comprehensive nature of the Common Hope benefit scheme distinguishes it from the cash transfer programs in three important ways. First, the direct interaction with social workers and other personnel from the project builds social capital in ways that the more anonymous cash transfers do not. Common Hope may be more able to influence the norms of the beneficiaries, and the personal nature of the support may add additional value to affiliation for families, beyond the direct monetary value of the services. Second, the provision of services allows Common Hope to provide benefits that vary in value, and can be targeted to those most in need. The families are expected to take some initiative and responsibility in seeking out various services, but with the help and guidance of the social workers, Common Hope is able to devote more resources to families in greater need. Lastly, the program is able to respond with extra assistance when families or individuals experience shocks that might otherwise force them to terminate the schooling of their children, or cause other hardships.

This idea of targeted benefits of variable sizes is one that should be of great interest to those designing conditional transfer programs, as there is a constant effort to improve efficiency and effectiveness of these initiatives. One major concern from an efficiency standpoint is that a uniform cash transfer across an entire rural, poor population may be in excess of the amount needed to induce enrollment for some families, and not enough for others. The concept of variable transfer sizes targeted based on risk factors was proposed by Raymond and Sadoulet (2003), but while this idea may be theoretically appealing and implementable, the social and political ramifications of variable cash payments could make this type of scheme problematic. Variable support in term of emergency assistance, health care, or housing might be more socially feasible, and seemingly less arbitrary.

Because the benefits of Common Hope accrue to the entire family conditional on the enrollment of only one child, it is difficult to incentivize the education of the other

children in the family, particularly those children who have never been directly sponsored by the program. These children will be referred to as “siblings” throughout the subsequent discussion and analysis. Keep in mind that “sibling” will refer only to those children in the household who have never been affiliated, and does not apply to other affiliated siblings of affiliates.

The impact of treatment on the attainment of unaffiliated siblings could be subject to both income and substitution effects. Assuming that education is a normal good, affiliation effectively increases income which should lead to an increase in demand for the education of all children. However, affiliation also decreases the price of education for the affiliate relative to their siblings. To the extent that education of one child is a substitute for education of another, changing the relative prices will lead to a decrease in demand for education of siblings and an increase in demand for education of affiliates. Because the income and substitution effects work in opposite directions, the net effect is indeterminate.

Describing the Sample

In order to quantify the impact of the Common Hope program on the mean attainment within the treatment group, a household level survey was conducted in July 2004. The survey included both treatment and control groups in order to compare the enrollment and attainment of affiliates with that of a comparable group outside the reach of Common Hope. This analysis will be concerned with the subset of treatment (130 households) and control (50 households) who had children aged six to nine in 1994, in order to ensure that we have a sufficient number of older students to analyze the long term impacts of the program.⁶

⁶ Common Hope operates in 15 villages outside of Antigua, Guatemala. The survey was conducted in the two most populous of those villages: San Juan del Obsipo and San Pedro las Huertas. These two communities have a more dense population and a more developed infrastructure of roads and buses than the other villages, some of which are perched on hillsides further from any commercial areas, consist of more marginal housing connected by dirt paths or impassible roads, and are characterized by what appears to be a relatively lower level of wealth. Although the survey data do not represent a random sample of the entire Common Hope treatment population, it is reasonable to believe that the educational impacts of the program are at least as significant in the other 13 communities. Evidence in this direction is provided by work on PROGRESA by Raymond and Sadoulet (2003), who showed that the conditional transfers had a greater effect on those who lived further from school. Because the other communities are more remote and poorer,

The control surveys were conducted in two villages about ten miles from the area served by Common Hope. These two villages, San Lorenzo and Tisate, were chosen because they were outside the reach of Common Hope, were not served by any other large scale NGO, and were in similar proximity to both Antigua and Guatemala City and the employment markets offered by those cities. A pre-questionnaire was used to screen for families of a comparable wealth level to affiliates, as well as ensuring that children in the 16-19 age group were sufficiently represented in the control households.

In choosing a control group, we wanted to be sure that the treatment group was at least as poor as the control sample in 1994. Descriptive data suggests that: 1) based on wall and floor materials it appears that the Common Hope sample started out a bit behind the control group; and 2) in terms of income and assets, the treatment group was similar, or slightly worse off in 1994. Sample selection leads to differences in the incidence of single parenthood, and larger family sizes on average, but if anything these are risk factors which would lead us to expect a lower level of education among the treatment group in absence of the program. Because the control might have been slightly wealthier than the treatment in 1994, their baseline level of education will provide a conservative comparison for the treatment effects. If our control sample had erred on the side of being too poor, comparison between treatment and control would have yielded a less credible and perhaps overstated estimate of the treatment effect.

Modeling and Estimation

The fundamental basis for economic modeling of investments in human capital continues to be the utility maximization framework (Becker and Tomes, 1976; Glewwe and Jacoby, 2004; Schultz, 2001). We will also view the schooling decision as a utility maximization problem where a unitary decision maker is responsible for choosing the amount of schooling received by each child to maximize household utility. Following much of Haveman and Wolfe (1995) the amount of schooling that maximizes utility is dependent on the size of the household, their means of earning income, their initial level of wellbeing, the number of children, their birth order and gender, mothers education,

application of this principle leads to the likely supposition that the impacts of the program on unsurveyed families equal or exceed those in the study sample.

single parenthood and a variety of wealth related factors (Table 1). We also hypothesize that education will be impacted by affiliation with the Common Hope program. In the following paragraphs we lay out the econometric techniques in greater detail

Table 1: Summary of Variables used in Regression

Variable	Description	Mean	St. D	Min	Max	Exp. Sign
<i>gender*</i>	=1 for males	0.488	-----	0	1	-
<i>schoolm</i>	number of years or education of the female household head	3.007	2.786	0	13	-
<i>singlep*</i>	=1 for single parent families	0.154	-----	0	1	+
<i>agwrkrs</i>	number of agricultural workers in the household	0.346	0.647	0	4	+
<i>bike94*</i>	=1 if family owned a bike in 1994	0.378	-----	0	1	-
<i>home94*</i>	=1 if family owned their home in 1994	0.644	-----	0	1	-
<i>totkids</i>	number of children in household	5.158	1.942	1	10	+
<i>peeps94</i>	number of people living and eating in household in 1994	6.936	2.752	2	20	-
<i>oldest*</i>	=1 for oldest child	0.300	-----	0	1	-/+
<i>Youngest*</i>	=1 for youngest child	0.146	-----	0	1	-/+
<i>margind</i>	index of marginality based on material of floor and walls, access to water, and smoke ventilation	5.638	2.567	0	10	+
<i>treatment*</i>	=1 for all members of treatment group	0.798	-----	0	1	-
<i>Affiliate*</i>	=1 for children whoa are or were directly sponsored by Common Hope	0.546	-----	0	1	-
<i>Siblings*</i>	=1 for all members of treatment group who have never been directly sponsored by Common Hope	0.229	-----	0	1	-/+

* indicates a dummy variable

Because we are interested in estimating impacts on attainment, the survey data include a large number of censored observations, observations for which we do not know the total educational attainment because the child is still enrolled in school. Duration

models are specifically constructed to analyze censored data. In this case, we are interested in the duration of school, or the time until termination of schooling. If the censored observations, were dropped from the analysis, a significant downward bias in the impact of the program would result. A similar bias results if these schooling spells are assumed to terminate at the date of the survey. Because we have data on children of different ages and at different points in their schooling trajectory, a duration model is a good choice because it allows simultaneous use of all of the data.

For this application, duration analysis yields an answer to the question: what is the probability of dropping out of school in period t , given that the student has been enrolled up to period t ? Duration models can be estimated using continuous or discrete time approaches; in the case of schooling, the schooling spell is a discrete time variable. Continuous duration data requires the researcher to choose a functional form which will reflect the duration dependence of the hazard rate (how the hazard rate in period $t+1$ is related to the hazard in period t), but discrete analysis allows us to incorporate a time varying hazard rate with no assumed functional form. This is beneficial because other evaluations have found that hazard rates are relatively steady throughout primary school, spike at the transition to secondary school, and then recover to lower, more stable levels (Raymond and Sadoulet, 2003).

Employing a continuous approach to discrete data also results in biased estimates because estimation methods for continuous time models, such as the Cox Proportional-Hazards model, require the ordering of observations based on time of failure. When many observations occur in the same time period, tied failures lead to problems in the estimation (Blossfeld et. al. 1989). It is tempting to employ a continuous approach because of the ready availability of continuous estimators in statistical packages such as STATA and LIMDEP, but this should be avoided.⁷

The strategy for estimation involves rearranging the data into a large panel, where each year of schooling for each child is represented by a separate observation (Allison 1982; Blossfeld et al. 1989; Fahrmeir, 1994). The dependent variable equals zero for

⁷ Although the discrete data duration technique is well suited to the evaluation of schooling, it has not been widely used in education literature. Raymond and Sadoulet (2003), and Glewwe and Jacoby (2004) do employ duration analysis to evaluate educational outcomes, but they use continuous data proportional hazard techniques not appropriate for the discrete data they examine.

each year that the child was enrolled, and one for the year that they drop out. We specify a functional form for the distribution of the hazard function, but we don't have to make any assumptions about duration dependence. The hazard rate is allowed to vary each period by incorporating a dummy variable, α_t for the grade level just completed.

Although it would be possible to incorporate time-varying covariates as independent variables x_{it} , we only have snapshots of information in 1994 and 2004. In order to capture the "baseline" as best we can, the data from 1994 are used, when available. Essentially, we use covariates from period $t=1$; only the grade dummy, α_t varies across time. In order to implement the model, the data must be expanded so that each observation represents only one year of schooling. A child who completed six years of schooling would be represented by seven observations in the expanded dataset, one for each year of completed schooling and one for the year where the event (dropout) occurred. A probit model is then estimated, using Y_{it} as the dependent variable. If a child is still enrolled (censored), then $Y_{it}=0$ for each of their observations; otherwise $Y_{it}=0$ for the completed years and $Y_{it}=1$ for the year when the child failed to enroll.⁸

Duration Model Results

In the following sections we implement the duration model in order to understand which variables exert a significant influence on school attainment, and to quantify the impact of Common Hope on the education of affiliates and their siblings. Our final goal is to empirically determine the change in expected attainment based on program participation. We estimate a number of different specifications of the model, some of which allow direct interpretation of the significance and magnitude of the marginal effects, and some of which feed into the calculation of hazard rates. First we utilize the set of variables from Table 1, along with grade dummies, to estimate the probit equations separately for boys and girls following Schultz (2003) and for primary and post primary school. In these models we are interested in comparing the significance of variables across gender and school level. We do not include interaction terms, because the interpretation of their sign and significance is not straightforward in the probit model, and we would like to gain direct insights that could be translated into policy implications. In

⁸ See Appendix B for the derivation of the Maximum Likelihood equation.

each table we aggregate treatment effects across the household (Model 1) and then decompose the treatment effects and look at affiliates and their never affiliated siblings separately (Model 2). These first specifications assume the treatment effect is constant over the schooling progression, and that all other covariates have the same impact for boys and girls. Next we relax these assumptions and interact the *treatment* variable with each grade in Model 3, and the *gender* variable with all other variables in Model 4, and the *affiliate/sibling* variables in Model 5. These estimates are used to calculate hazard rates by grade for control and treatment boys and girls. Using the estimated hazard rates, we then calculate the expected attainment for each group of children. The interaction terms allow us to calculate specific attainment levels for treatment and control, boys and girls, and affiliates and siblings.

Table 13 : Marginal Effect on Probability of Dropout, Primary School

d	Model 1		Model 2	
	dF/dx	z	dF/dx	z
gender*	0.000	-0.11	-0.001	-0.25
schoolm	-0.004	-3.59	-0.003	-3.53
singlep*	0.016	2.03	0.015	1.99
agwrkrs	0.010	3.94	0.010	4.08
bike94*	-0.020	-4.27	-0.020	-4.36
home94*	-0.004	-0.80	-0.004	-1.01
totkids	0.003	2.35	0.003	2.15
famsize94	-0.003	-2.51	-0.003	-2.91
oldest*	-0.001	-0.26	-0.002	-0.42
youngest*	0.010	1.52	0.007	1.14
margind	0.001	0.99	0.001	0.96
treatment*	-0.039	-4.97		
affiliate*			-0.032	-5.71
siblings*			-0.015	-3.25
second*	-0.019	-3.36	-0.018	-3.33
third*	-0.005	-0.92	-0.005	-0.86
fourth*	-0.005	-0.75	-0.004	-0.68
fifth*	0.001	0.13	0.002	0.27
sixth*	0.004	0.53	0.005	0.73

n= 3367	n = 3367
LR chi2(17) = 117.83	LR chi2(18)=127.03
Prob > chi2 =0.0000	Prob > chi2 = 0.0000
Log likelihood = -418.81	Log likelihood = -414.21
Pseudo R2 = 0.1233	Pseudo R2 = 0.1329

* indicates dummy variable

For the primary grades, all of the significant variables are of the expected sign, and again the magnitude of the treatment variable is larger than any of the other significant dichotomous variables. Not only is the effect of the treatment variable negative and highly significant, but it is driven by impacts on both the affiliates and their siblings.

Comparing the models for primary school and post-primary (Table 14), yields valuable insight into how various factors influence the schooling decision. Most notably, the dummy variable for the oldest child has a significant positive influence on dropping out in the post-primary grades while it was far from significant in the primary grades. Additionally, *home94*, the credit proxy, is only significant in the later grades. This confirms out intuition that as the costs of education rise, wealth/credit constraints become a limitation on further schooling.

Table 14 : Marginal Effect on Probability of Dropout, Post Primary School

d	Model		Model	
	dF/dx	z	dF/dx	z
gender*	-0.024	-1.12	-0.022	-1.06
schoolm	-0.006	-1.46	-0.006	-1.47
singlep*	0.026	0.79	0.033	0.99
agwrkrs	0.053	2.51	0.055	2.66
bike94*	-0.069	-3.14	-0.070	-3.23
home94*	-0.064	-2.64	-0.073	-2.95
totkids	0.003	0.49	0.002	0.28
famsize94	0.005	1.07	0.004	0.96
oldest*	0.040	1.71	0.029	1.26
youngest*	0.000	0.00	0.000	0.00
margind	-0.001	-0.23	-0.001	-0.29
treatment*	-0.036	-1.10		
affiliate*			-0.063	-2.07
siblings*			0.018	0.50
eighth*	-0.118	-5.29	-0.114	-5.13
ninth*	-0.138	-5.54	-0.135	-5.44
tenth*	-0.056	-1.99	-0.052	-1.85
eleventh*	-0.120	-3.81	-0.116	-3.66
twelfth*	-0.076	-2.04	-0.072	-1.91

n = 967
 LR chi2(17) = 106.36
 Prob > chi2 = 0.0000
 Log likelihood = -355.49

n = 967
 LR chi2(18) = 115.37
 Prob > chi2 = 0.0000
 Log likelihood = -350.98

Pseudo R2 = 0.1301

Pseudo R2 = 0.1411

*indicates a dummy variable

The overall treatment variable for the post primary years does not significantly reduce the probability of dropping out. Decomposing the effect, we see that affiliates are still positively impacted by Common Hope, but their siblings show an increased probability of terminating schooling. Although the effect for siblings is not significant, it is sufficiently strong to dampen the aggregate treatment effect in Model 1.

Table 15: Marginal Effect on Probability of Dropout, GIRLS ONLY

d	Model 1		Model 2	
	dF/dx	z	dF/dx	z
schoolm	-0.005	-3.00	-0.005	-3.19
singlep*	-0.004	-0.36	-0.002	-0.20
agwrkrs	0.010	1.99	0.010	2.08
bike94*	-0.035	-4.55	-0.035	-4.84
home94*	-0.018	-2.29	-0.019	-2.59
totkids	0.003	1.49	0.002	1.09
famsize94	-0.001	-0.67	-0.001	-0.89
oldest*	0.014	1.67	0.010	1.27
youngest*	0.024	1.79	0.016	1.28
margind	0.002	1.20	0.002	1.28
treatment*	-0.042	-3.50		
affiliate*			-0.048	-4.86
siblings*			-0.016	-1.82
second*	-0.026	-2.13	-0.025	-2.09
third*	-0.008	-0.60	-0.006	-0.45
fourth*	-0.006	-0.42	-0.004	-0.33
fifth*	0.002	0.12	0.005	0.31
sixth*	0.005	0.29	0.009	0.58
seventh*	0.245	8.03	0.260	8.27
eighth*	0.079	3.01	0.093	3.39
ninth*	0.012	0.47	0.019	0.72
tenth*	0.212	4.91	0.234	5.19
eleventh*	0.043	1.07	0.058	1.37
twelfth*	0.275	4.01	0.307	4.31

n = 2218

LR chi2(22) = 208.35

Prob > chi2 = 0.0000

Log likelihood = -404.50

Pseudo R2 = 0.2048

n = 2218

LR chi2(23) = 222.34

Prob > chi2 = 0.0000

Log likelihood = -397.51

Pseudo R2 = 0.2185

* indicates a dummy variable

Tables 15 and 16 estimate the covariates for males and females separately. These results have important implications for the design of benefits for girls and boys affiliated with the program, and the potential for variations in benefits across gender. The factors that exert significant influence over the education of girls and boys are somewhat different. The influences on the decision to drop out for boys are centered on economic issues which reflect a high opportunity cost of enrollment. Most notably the single parent effect is a positive and significant (99%) influence on the probability of dropping out for boys, while for girls it is not only insignificant, but negative. Additionally, the

Table 16: Marginal Effect on Probability of Dropout, BOYS ONLY

d	Model 1		Model 2	
	dF/dx	z	dF/dx	z
schoolm	-0.004	-2.80	-0.004	-2.54
singlep*	0.056	3.32	0.051	3.16
agwrkrs	0.018	3.71	0.019	3.90
bike94*	-0.022	-2.92	-0.020	-2.74
home94*	-0.017	-2.04	-0.019	-2.27
totkids	0.002	0.99	0.002	0.70
famsize94	-0.001	-0.54	-0.001	-0.70
oldest*	-0.001	-0.08	-0.001	-0.12
youngest*	0.001	0.13	0.000	-0.04
margind	0.000	-0.11	0.000	-0.19
treatment*	-0.043	-3.49		
affiliate*			-0.036	-3.76
siblings*			-0.015	-1.57
second*	-0.032	-2.72	-0.032	-2.71
third*	-0.010	-0.78	-0.009	-0.77
fourth*	-0.011	-0.83	-0.010	-0.82
fifth*	-0.004	-0.28	-0.003	-0.21
sixth*	0.002	0.12	0.003	0.23
seventh*	0.205	7.35	0.210	7.40
eighth*	0.033	1.53	0.038	1.69
ninth*	0.020	0.86	0.023	0.95
tenth*	0.106	2.89	0.113	3.00
eleventh*	0.005	0.14	0.008	0.23
twelfth*	0.006	0.15	0.008	0.21

n = 2116
 LR chi2(22) = 167.16
 Prob > chi2 = 0.0000
 Log likelihood = -371.68

n = 2116
 LR chi2(23) = 169.82
 Prob > chi2 = 0.0000
 Log likelihood = -370.35

Pseudo R2 = 0.1836

Pseudo R2 = 0.1865

*indicates a dummy variable

magnitude of the impact of single parenthood for boys is greater than the treatment effect, indicating that affiliation with the program does not overcome the risk associated with living in a single parent household for males. Although other wealth variables are also significant for girls, another distinction arises in the birth order effects. The birth order variables are far from significant for boys, but being the *oldest* or *youngest* positively influences the probability of dropout for females. These results reflect the intuition that there are demands for the oldest daughter to work in the household, while male children succumb to pressure to work outside the home, especially when they come from single parent households.

The treatment variable is significant for both boys and girls at the 99% level. When the treatment variable is broken down by affiliation status we again see that never affiliated siblings benefit from the program (the sign is negative) but the magnitude is small and it is only significant at the 90% level for girls, and below 90% for boys.

Expected Attainment and Estimated Hazard Rates

In order to generate estimated hazard rates and expected attainment across groups, we run the model using interactions between affiliation, gender and grade. These interaction terms allow the hazard rate to vary by gender, grade level, and affiliation status. Three additional models were estimated to obtain the predicted hazard rates and expected attainment. The first, Model 3, used the base model and interacted *treatment* with each grade dummy to allow differential program impacts throughout the schooling progression. The second, Model 4, added *gender* interaction with ALL terms including the *treatment*grade* interaction. This allows different hazard rates, by grade, for girls and boys in the treatment and control groups, as well as different coefficients on all of the other variables based on gender. Lastly, Model 5 interacts both *affiliate* and *sibling* rather than *treatment* with the grade dummies, and includes gender interaction for all variables. Each of these specifications gives us distinct and important insights into the impact of the program.

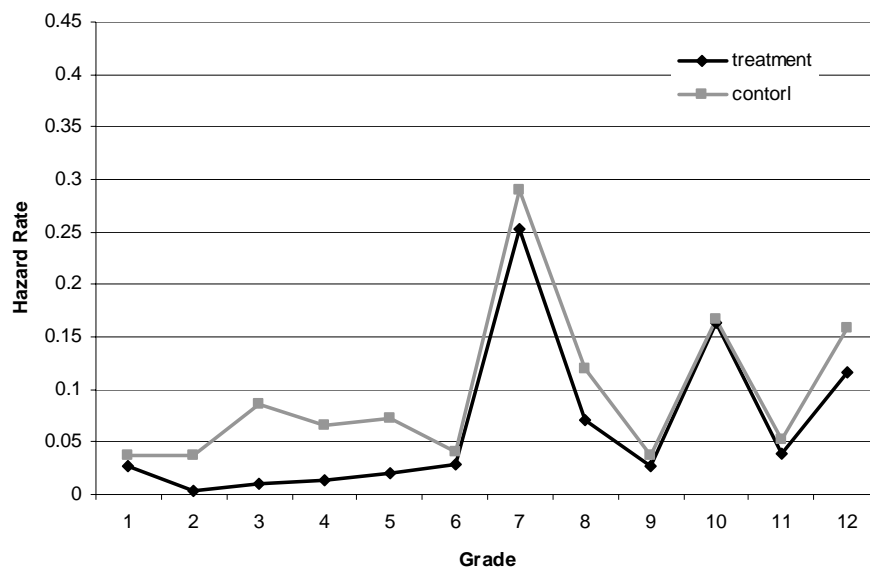
To obtain the estimates of the hazard rate for grade t , h_t , we apply the estimated coefficients to the means of the data. The product of all the hazard rates up through year t gives the expected value of one year of education in year t , or the overall probability of completing year t . Summing these values yields the expected value of attainment.

$$E(\text{Attainment}) = h_1 + h_1h_2 + h_1h_2h_3 + \dots + h_1h_2h_3\dots_{12} \quad (15)$$

The operation is performed for each combination of gender, affiliation status and grade level, in order to obtain separate estimates of hazard rates, overall probability of completion and expected attainment for each subgroup.

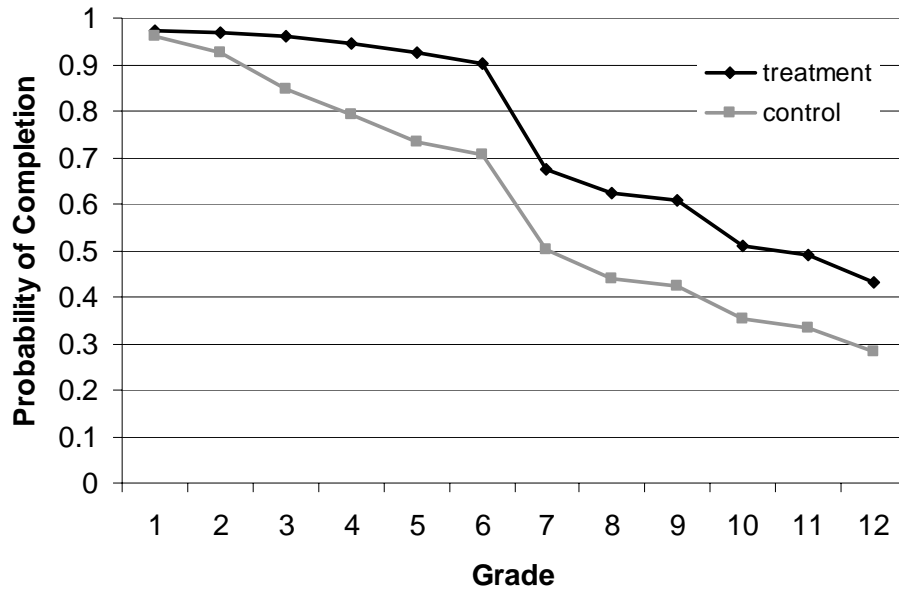
In Figure 12 we see that the hazard rates for the treatment are consistently lower than the control through primary school, but the difference is less pronounced after fifth

Figure 12: Estimated Hazard Rates, Treatment vs. Control



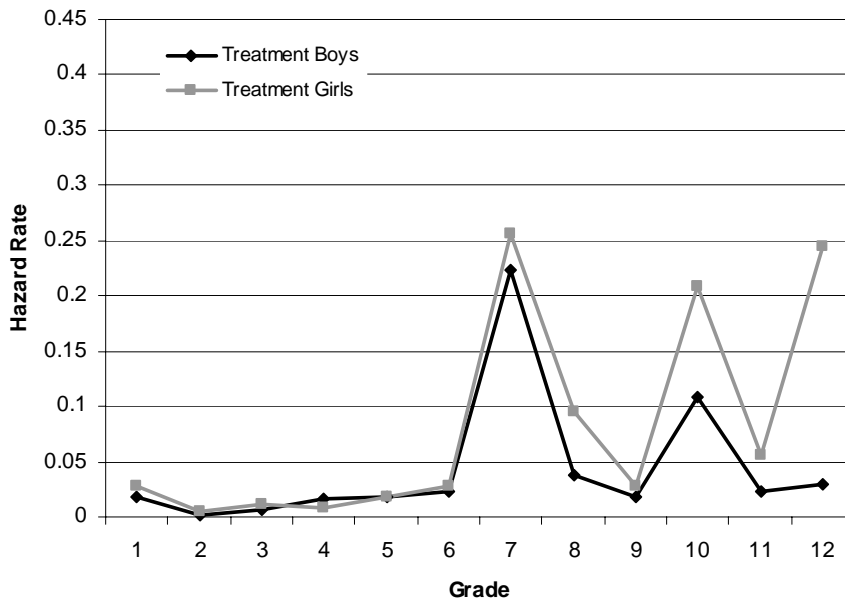
grade. The difference in hazard rates between the two groups can be interpreted as the direct effect of program participation as estimated in our model, since the estimates were generated by holding all other factors constant and varying only the treatment effect for each grade. Aggregating all children in the household with the treatment variable, we see that Common Hope has a positive or neutral impact on the grade to grade progression of the average child. Figure 13 graphs the overall probability of completing each grade.

Figure 13: Probability of Completion



This representation clearly demonstrates how the major divergence between treatment and control happens in the primary years, and that early impact is sustained throughout the life of the child, increasing the probability of completing all grades.⁹

Figure 14: Hazard Rates within Treatment based on Gender

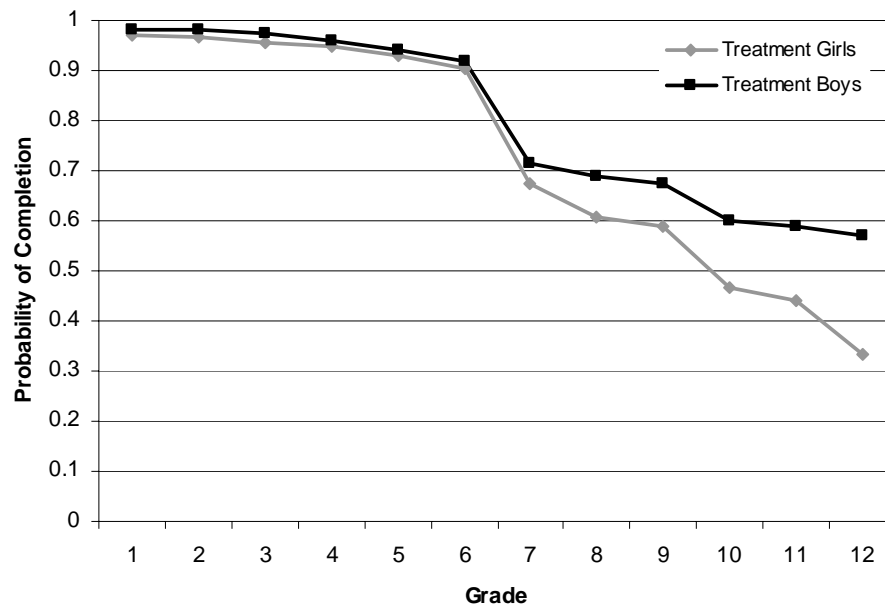


⁹ Note that in Figure 13 the hazard rates for a given year are simply the opposite of the slope between two consecutive points.

The aggregate comparison between treatment and control is instructive; we see that Common Hope has a positive impact on the way that families make choices about education for the representative child. Figures 14 and 15 compare girls and boys within the treatment sample, allowing us to see differences in the way the program impacts the gender gap. We are still aggregating affiliates and their siblings into the treatment group, so these figures indicate the overall impacts on boys and girls within treatment households.

In Figure 14, there is a striking difference in the primary and post primary gender trends. Girls and boys drop out at nearly identical rates through primary school, but the hazard rate for girls is much more erratic in the post-primary years. When we look at the

Figure 15: Completion Probabilities by Gender

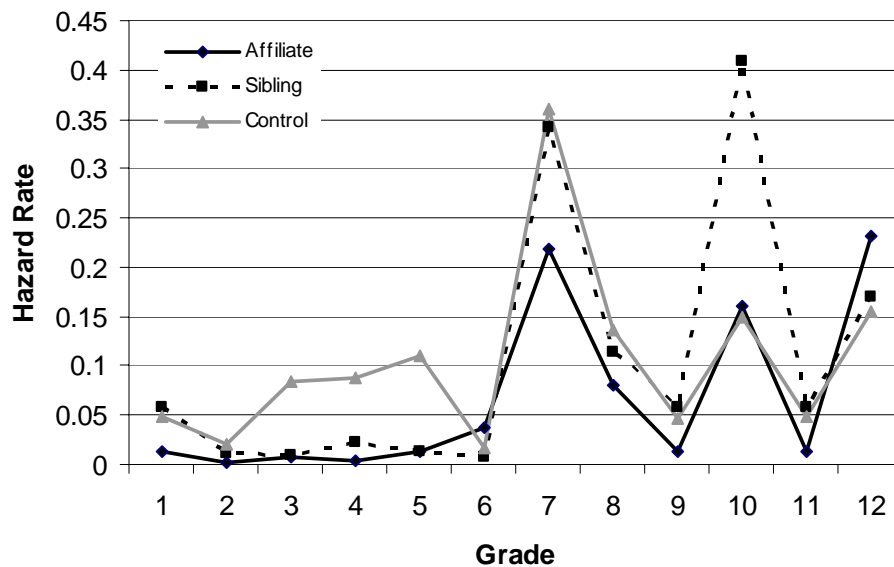


probability of grade completion, in Figure 15 there is a marked divergence after seventh grade. Boys living in treatment households are almost 25% more likely to complete high school than their sisters.

Next we break down the sample by both gender and affiliation status. Figures 16-19 show the hazard rates and completion probabilities estimated from Model 5, which incorporated grade and gender interactions with the *affiliate* and *sibling* variables. The effect of household program participation on female siblings in the household is nearly

indistinguishable from affiliated females through primary school, but in the middle school and high school grades the female siblings drop out at rates as high or higher than the control (Figure 16). In Figure 17 we see that these post primary hazard rates are not sufficiently high to negate the strong, positive impact in primary school. Siblings of affiliates have a higher probability of completing all grades through 9th, and the same probability of completing high school as their female counterparts in the control group. Overall, there is a strong, positive impact on the probability that female siblings will complete primary school and middle school, but no impact on their completion of high school.

Figure 16: Hazard Rates for Females



The within treatment trend for boys is similar to that for girls. Again we see in Figure 18 that the primary school hazard rates are very similar for affiliates and siblings, but after primary school the siblings see significant dropout in the transitions into middle school and high school. However, it is only in the transition years that the male siblings are at risk; in 8th, 9th, 11th and 12th grades they have lower hazard rates than the control, and comparable to affiliates. Figure 19 shows that male siblings have higher probabilities of completing all grades through high school.

Figure 17: Probability of Grade Completion for Females

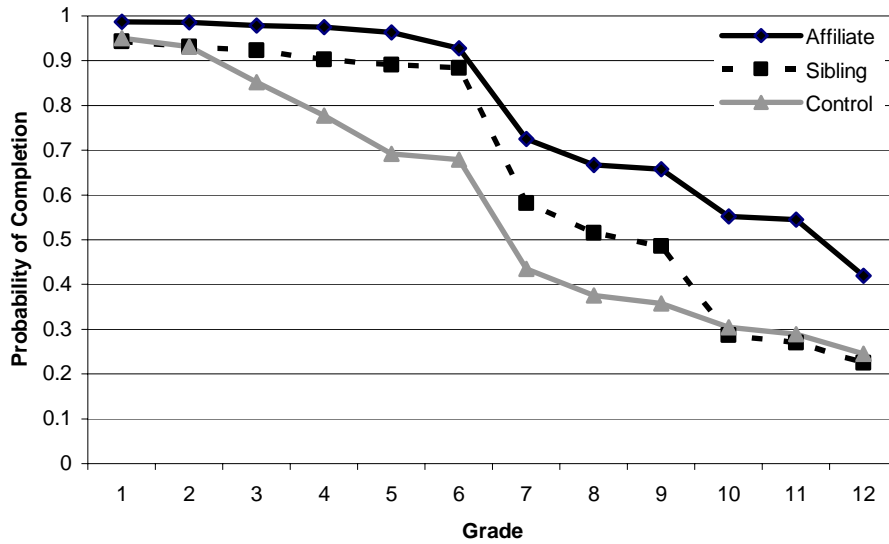
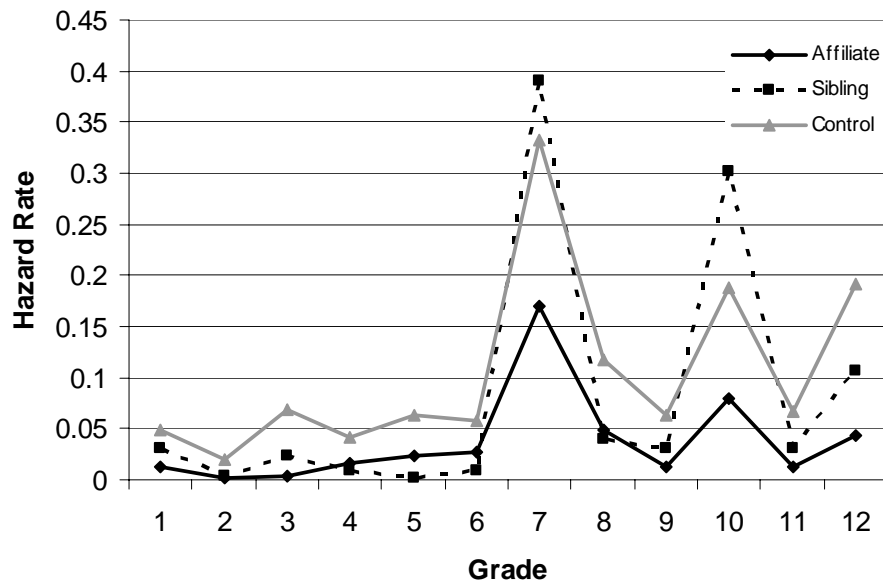


Figure 18: Hazard Rates for Males

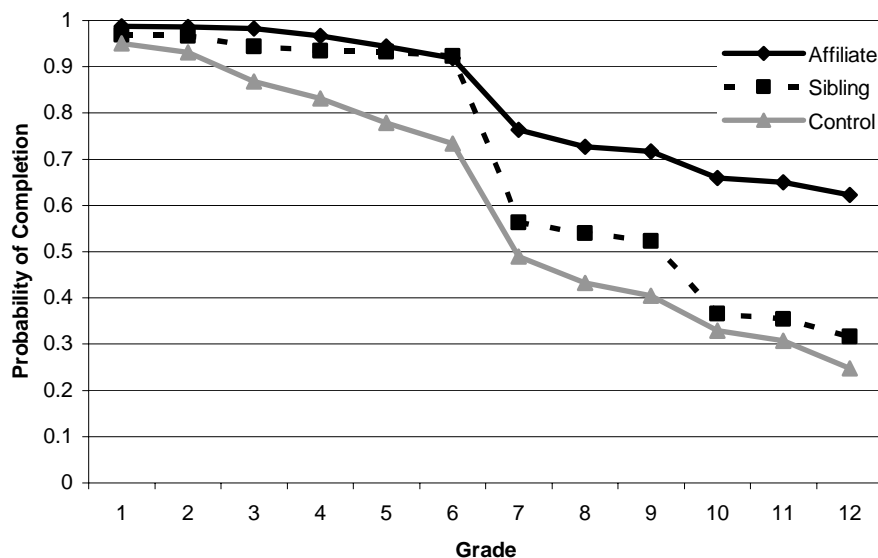


A second difference between the effects on boys and girls arises in the case of male affiliates. They have significantly lower hazard rates than the control throughout the entire schooling progression, whereas the impact on affiliate girls was more muted in the post primary years. This indicates that the Common Hope benefits are valuable

enough to impact the education of male affiliates at all levels. In Figure 19 we see that the lowered hazard rates for affiliate boys open up a very significant gap with their male counterparts in the control in terms of the probability of grade completion. Affiliates have a 62% probability of completing high school, compared to 25% in absence of the program. Looking back at Figure 17, we see that the comparable probabilities for girls are 42% for affiliates and 23% in the control. The impact of Common Hope on the probability of completing high school is much stronger for boys than girls, and opens up a gender gap that is small in absence of the program.

The graphical representations of hazard rates and completion probabilities have been instructive in understanding how the impacts of the program are distributed over the different groups throughout the schooling progression. Next we calculate expected attainment using the above hazard rates, which gives us the most concise estimates of the program impact.

Figure 19: Probability of Grade Completion for Males



The expected values of attainment are reported in Table 17. On the aggregate level, participation in the Common Hope program implies an expected attainment of 9.01 years of schooling, compared to 7.30 in the control (Model 3). This translates to an extra 1.7 years, or a 23% increase in attainment, on average, across the entire household. The children who are actually sponsored by Common Hope (affiliates) experience even

greater increases in expected attainment, 36% for both male and female affiliates, relative to their counterparts in the control (Model 5).

Table 17: Expected Attainment

		Control	Treatment	Percent Change Relative to Control
Model 3	Household Total	7.30	9.01	23%
Model 4	Girls	7.03	8.79	25%
	Boys	7.40	9.59	30%
Model 5	Female Control	6.88		
	Female Affiliates		9.38	36%
	Female Siblings		7.84	14%
	Male Control	7.30		
	Male Affiliates		9.92	36%
	Male Siblings		8.33	14%

Table 17 also reports expected attainment by gender at the household level (Model 4). There is small gender gap in attainment in the control group, which boys getting about 0.4 more years of education than girls. However, the treatment effect is stronger for males than females, and treatment opens up a larger gender gap than is present in the control, resulting in 0.7 more years of education for boys in the treatment group. In Model 5 both males and females get the same percentage increase in attainment. Regardless of whether the impact on males is statistically different from that for females, there is no evidence that Common Hope closes the existing gender gap.

Throughout the analysis we have been concerned about the outcomes for siblings of affiliates. Table 17 shows a 14% increase in expected attainment of both male and female siblings. We have interpreted the impact on siblings as determined by the relative magnitudes of the income and substitution effects of program participation, since benefits are not conditioned upon their enrollment. These numbers lead us to believe that the income effect is dominant, and probably accounts for the increase in attainment among never affiliated siblings. It is also possible that affiliation with the program leads to changed norms within treatment households, which impact their decision making. In any case, it is very encouraging to see a positive, if smaller, impact on the education of children within the household for whom schooling carries no conditionality. A negative impact would have been difficult to interpret based on the possibility of sample selection

bias, but the positive impact can unambiguously be interpreted as the influence of the program.

In order to put the above attainment figures in a larger context, recall that Raymond and Sadoulet (2003) found that PROGRESA increased expected attainment of program participants by .66 years, which was a 9% improvement over the control. Our estimate of the size of Common Hope benefits as a proportion of household income was similar to the proportional size of the cash payment in the Mexican program. With similarly valued benefits, Common Hope achieves a 23% increase in enrollment. This provides strong evidence that the comprehensive nature of the Common Hope program compounds the strict monetary value of the benefits.

In an effort to quantify the influence of rising incomes, Glewwe and Jacoby (2004) study the covariates of schooling in Malaysia, and model the expected increase in education yielded by a 50% increase in household income. They predict that a 50% increase in income would result in an increase in expected attainment from 7.5 to 7.8 years, or a 2.6% increase in attainment. Some component of increased attainment in the Common Hope treatment group is sure to be due to the income effect of the benefits and the conditionality imposed upon affiliates, but the relatively small impact of income in the Malaysia study suggests that the alleviation of opportunity costs, increased social capital, and perhaps the efficient targeting of benefits are all part of the impact of Common Hope. The increase in attainment for siblings is especially notable in this light. It is unlikely that the 13% increase the expected education of siblings is due solely to the approximately 37% increase in household income.

We may not be able to directly compare the impact of Common Hope to programs in other countries, however the magnitude of the increase in expected attainment is striking when compared to the estimated impacts of conditional cash payments and income augmentation in other countries. There is reason to believe that the comprehensive nature of the Common Hope benefit structure impacts both the effective income of families and their norms about the value of education, as well as providing potentially valuable social ties and interactions whose costs are not embodied in the monetary expenditures of Common Hope. The individualized support, personal relationships, and empowerment that affiliate families develop through the program may

be the key components in explaining the large impacts we see on the education of all children in affiliate families.

Conclusions

The fundamental questions driving this research have been: 1) what are the educational attainment impacts of Common Hope; 2) how can the Common Hope program be modified in response to what we know about the logic, design and implementation of large scale conditional transfer programs; and 3) what recommendations can be made to improve the efficiency of future large scale CTT programs, based on the analysis of Common Hope. The first question was addressed in Chapter 5, and the second and third will be dealt with here.

First we motivated this discussion by reviewing the theory and empirical evidence that lead the development community to put such a strong focus on improving educational attainment as one component of “development”, conceived broadly. We then looked at the different strategies that have been employed in trying to achieve the goal of increased enrollment and attainment, drawing a distinction between strict supply side approaches and newer interventions that also target demand. Summarizing the design of some of the large scale CTT programs, PROGRESA, RPS, PRAF, and FFE set the stage for thinking about Common Hope in terms of the logic of conditionality, and the incentives that arise from conditioning benefits on education.

After describing the details of affiliation with Common Hope and the benefits available to affiliated households, we turned to a discussion of the data. We looked at a variety of descriptive statistics capturing information about the treatment and control groups, and came to a better understanding of how they are similar and how they differ. A discussion about the theory behind modeling educational outcomes was followed by discussion of the econometric techniques employed in the analysis of Common Hope, and the specific variables we use in the model. The duration analysis employed here represents an important contribution to the methodology for assessing program impacts in the area of education.

Descriptive data and some preliminary probit regressions on enrollment, completion, continuation, and repetition drew our attention to the possibility of differential impacts of the program based on grade, gender, and affiliation status within

the treatment households. These issues were all explored in more detail using the duration model, and we were able to generate expected attainment values that accounted for variation on these measures. The effect of participation in Common Hope on the mean expected educational attainment in treatment families is substantial; the program leads to an increase in expected attainment of 1.7 years, or a 23% increase over non-participants. We were also alerted to a larger gender gap between attainment of affiliates than would be apparent in absence of the program.

The analysis in the preceding chapters lends insight into both the specific risk factors associated with the schooling decision, and the ways that educational outcomes for treatment families are impacted by the incentive structure of Common Hope. Here we first explicitly draw out the implications of some of these results for the design of the Common Hope targeting and benefits structure. As with any development initiative, Common Hope suffers from tight budget constraints, and a more careful consideration of the economic incentives provided by the program in light of the available data and the results of this analysis could lead to an improvement in efficiency of the program. We then discuss the larger CTT programs in light of the comprehensive conditional transfers offered by Common Hope, concluding with a discussion of the relative merits of cash and comprehensive transfers.

Four recommendations for possible modification to the Common Hope benefit structure arise out of the results of this study:

- 1. Address high rates of repetition among affiliates by: 1) encouraging children to enroll in first grade at age 7 rather than 6, to reflect the local norm; 2) extending full affiliation benefits through 7th grade for students who have not repeated any grades in primary school.***

High rates of repetition among affiliates are costly for Common Hope, for the families, and possibly for the educational success of the child. It is possible that grade repetition is influenced by the institutional practice of encouraging enrollment at age 6, or by a strategy of delay in order to maximize benefits. A third possibility is that affiliated children may repeat rather than dropping out of school when they fail a grade. In this case high rates of repetition simply reflect lower rates of dropout in primary school. By concurrently changing the age at entry policy, and extending the benefits into middle school, Common Hope might be able to combat any potential distortion of incentives that

leads to high rates of repetition. These measures would further ensure that high rates of repetition among affiliates are due to the luxury of giving students who fail a second chance, rather than a result of distortions caused by program design and policies.

Extending the benefits of full affiliation contingent upon year-to-year grade progression in elementary school, the incentives for strategic delay are averted. Grade repetition is costly for Common Hope, because it extends their obligation to full affiliates for an extra year. It is costly for students because they may lose interest in school, are overage for their grade, and a year passes in which their attainment is not advanced, but during which their opportunity costs are increasing. Translating these costs into extra education for the affiliate improves efficiency of the program, and results in a better outcome for affiliates and the schools they attend. If families can look forward to seven years of benefits, they are better off encouraging their children to progress through the grades so that at the end of those seven years educational attainment is maximized.

An additional benefit of extending the benefits of affiliation into 7th grade is that once a student starts junior high they may be more likely to finish. We saw in Figure 12 that the aggregated hazard rates within treatment households are not different from the control in post-primary years. If there are spillovers from increasing seventh grade enrollment onto 8th and 9th grade enrollment, the impacts of the program will be further augmented. Additionally, the extension of benefits will bolster the income effects of the program, increasing the likelihood of enrollment for siblings. Extending affiliation might be a way to address both strategic delay, and the post-primary impacts.

2. Specifically target affiliate status to the oldest and youngest girls in the family, and to boys from single parent households.

Modifications to the targeting policies could also improve the program design. We saw in Tables 16 and 17 that boys from single parent families face a high risk of dropping out, as do the oldest and youngest girls in any family. Multiple children in the same family often earn affiliation. If Common Hope specifically targeted boys for sponsorship in the single parent households, and targeted the oldest and youngest girls in all households, they might be able to mitigate these risk factors.

3. Only pay the education expenses for children after fourth grade.

Because the current design of Common Hope initiates benefits starting in first grade, it risks over-coverage; the program pays the educational costs of children who would be enrolled regardless of affiliation status. Rates of enrollment are already relatively high in primary school, and it may be possible to achieve the same gains by starting benefits later in the schooling progressions. One possibility would be to offer full affiliation benefits to families, but *not* pay the educational costs of children below the 4th grade. Families would still receive the valuable health, housing and family development support, and that support would still be conditional on enrollment. If the education benefit started in fourth grade significant savings would result that could be put towards distributing the benefits more equally among children in the household or extending the benefits to later grades. The expectation of future benefits combined with the conditionality of other services would likely be enough to induce enrollment in the first three grades of primary school, especially since enrollment rates in these years are already quite high.

4. Augment the post-primary benefits for females by covering the full direct costs of schooling or augmenting benefits with a small monthly cash transfer for post-primary females.

The last recommendation specifically addresses the post primary effect on girls in treatment households. Augmenting the benefits for girls in the post primary years is the most straightforward way of impacting these outcomes. Because families face the potential (although flexible) revocation of full affiliation after primary school, the expected benefits from affiliation decrease just as both direct and opportunity costs increase. Girls are pulled from school at this point for one of two reasons; either their opportunity costs increase relative to boys, or the expected returns to further education decrease. The “beca” or Scholarship affiliation in post-primary grades does not currently cover all of the costs of education; increasing this benefit to cover the full direct cost would be a starting point. Additionally, Common Hope could employ a small monthly cash transfer paid to the mothers of girls enrolled in middle school or high school. These strategies appeal because the benefits are individually conditional; no substitution is possible within the conditionality framework. Common Hope has the institutional

infrastructure to implement a cash payment, there is already a detailed system for receiving reimbursements for educational expenditures, and these reimbursements could simply be augmented. The increased gender gap in expected attainment and completion of high school is socially problematic, and needs to be addressed.

Common Hope faces a variety of options in modifying or redesigning the benefits structures and targeting of the program, based on intuition about the logic of strategic decision making, and our knowledge of the outcomes of the existing structure. It is also clear that the program has significant and positive effects on overall enrollment and attainment in aggregate, and that these effects extend not only to affiliated children of both genders, but also to their siblings. The duration analysis in Chapter 5 allowed us to see differential impacts of the program based on grade level and gender, but in thinking about how to modify the design of the program, we should not lose sight of its overall positive impact on education within affiliated families. That Common Hope is able to achieve a strong, positive impact on boys and girls, affiliates, and their siblings, is an impressive achievement. That the overall increase in expected attainment is 23% compared to a 9% impact for PROGRESA is equally striking.

Throughout this analysis we have been careful to look specifically at the siblings of affiliates in order to detect any negative impacts on their educational opportunities due to substitution. In the regression analysis we saw mixed results in terms of a significant *positive* impact on siblings, but there was never any evidence of any type of negative impact (statistically significant or otherwise). We saw in Chapter 5 that the hazard rates for both male and female siblings are effected positively by affiliation throughout primary school, and that this impact carries over into a weak positive or neutral affect on the probability of completing the post primary grades. In some ways this result is surprising from the standpoint of economic theory. Because conditionality did not extend to the siblings of affiliates, we expected to find some evidence of substitution, however the positive impact on siblings was strong enough to sustain throughout their education. It is likely that the income effect of affiliation can explain this result to some degree though Glewwe and Jacoby (2004) found that income had a much more modest impact on expected attainment. We suspect that changing norms within the household also play a part in increasing the attainment of siblings, and that this factor may also drive much of

the impact on affiliates as well. This is perhaps the most surprising and important finding of the study. If the comprehensive benefit structure and personalized nature of the Common Hope program have a stronger impact than the equivalent cash value of the benefits, this is strong support for the comprehensive Common Hope strategy. We are in no position to quantify these normative impacts, but the outcomes we have found suggest the need for additional inquiry in this area.

Some further comments are in order regarding the relative merits of a comprehensive program like Common Hope compared to direct cash transfers. There are surely some benefits to cash transfers: fewer resources have to go into bureaucracy; the benefit is impersonal, and less prone to harboring personal resentment due to perceived favoritism; implementation of the program is much simpler; and the program can operate more easily on a very large scale. However, there are also significant benefits to a comprehensive benefit design. Because there is no maximum transfer amount, the poorest of the poor can be included in the program, not priced out by small transfer sizes. The possibility of variable levels of service or assistance introduces the potential for greater efficiency in targeting the value of benefits. Although Raymond and Sadoulet (2003) propose an “implementable” scheme of variable-sized, risk-targeted transfers, the political and social ramifications of varied cash payments would be significant. Seemingly arbitrary distinctions between neighboring households that resulted in different sized payments could easily create resentment and ill-will. However, helping a family to replace their leaking roof with a new one, or install ventilation for their cookstove, is probably more readily accepted in the community. Providing an array of comprehensive services on such a national scale is also impractical, but a program that covered schooling costs and conditioned health insurance, food security, and a few housing improvement projects based on school enrollment could take advantage of the potential for more efficient targeting.

Lastly, the Common Hope program acts as insurance against major shocks in a way that cash transfers may not. Although a steady monthly cash payment is a source of income that is not susceptible to exogenous shocks like droughts or hurricanes or health emergencies, the fixed payment does not allow families to adequately respond when their situation is negatively impacted in severe or extreme ways. Common Hope is

specifically designed to mitigate shocks like this; a major injury, illness or accident, a bad harvest, or a robbery in the family store could be enough to force children out of school to contribute to family income. Common Hope is able to act as insurance against the outcomes of these types of extreme shocks. That flexibility may be of special value to very poor households, and seems worthy of further exploration in the design of CTT studies.

Guatemala is only one among many developing countries yet to achieve universal primary education. This analysis provides hope that the goal is within reach, not only in Guatemala but across the developing world. Demand side interventions like the CTT programs across Latin America have proved to be an effective and efficient means of achieving educational gains, and these programs have not yet been implemented in some of the poorest countries of Asia and Africa. Additionally, the extremely large impacts of Common Hope indicate that there may be complementarities to investment in education that are yet untapped in the existing CTT programs. In particular, there is reason to believe that the large impact of Common Hope on siblings of affiliates cannot be explained solely as an income effect, but may also embody the impacts of increased social capital, the value of personalized support and empowerment, and changing norms about the benefits of education. If policy makers effectively use the tools of demand side interventions, and recognize the potential to augment existing gains by incorporating more comprehensive elements into the programs, we believe that the goal of universal primary education will not remain an elusive ideal.

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Appendix A

Figure 1: Walls made of Cement Block or “Fibrolit” (% of households)

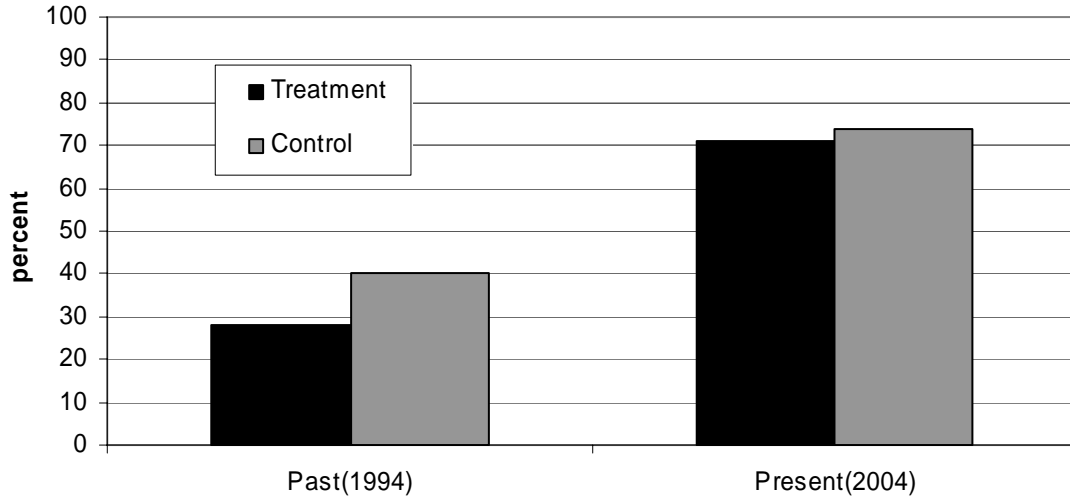


Figure 2: Dirt Floors (% of households)

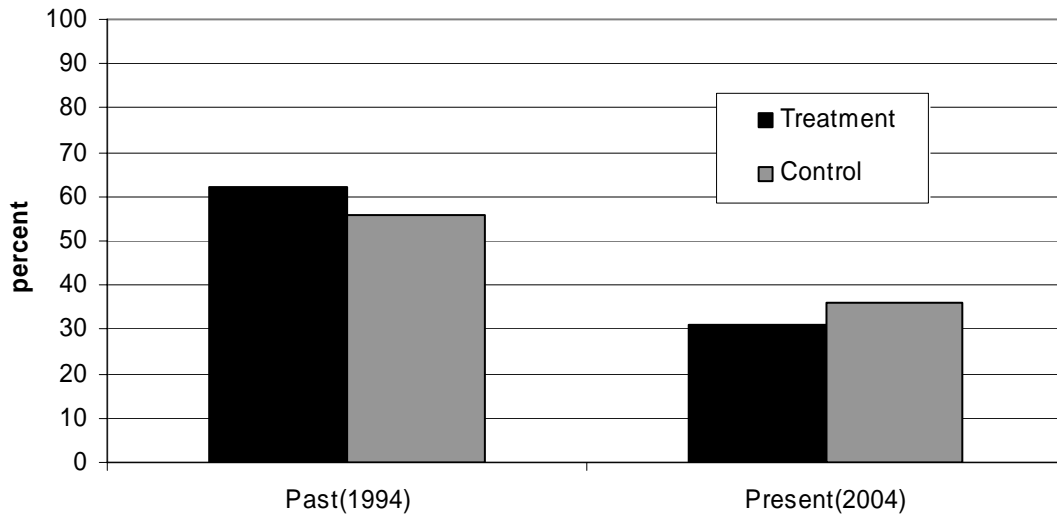


Figure 3: Piped Water (% of households)

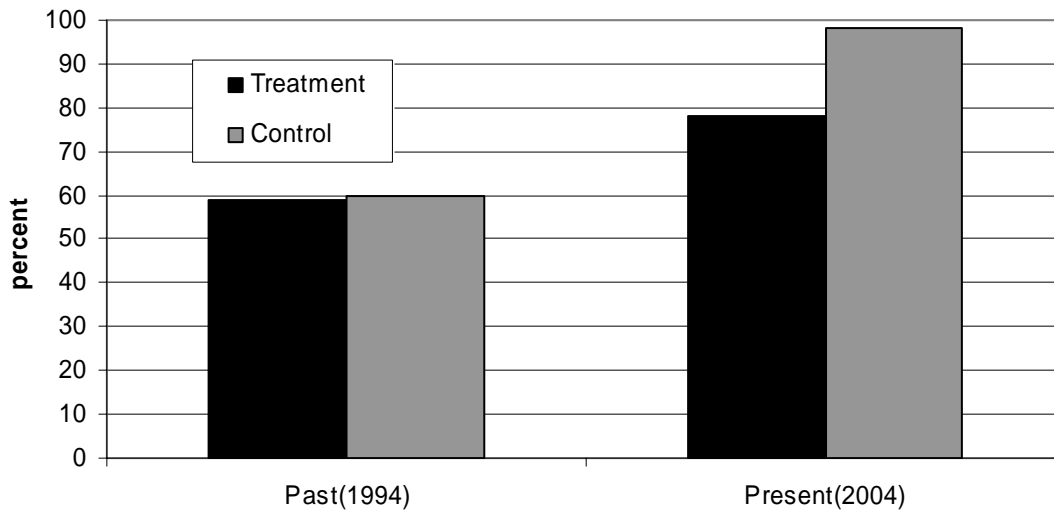


Table 1: Per Capita Income (Quetzales)

Year	Treatment	Control	T-test	Significance
1994	1822.30	2068.2	0.757	0.451
2004	3535.27	3105.6	1.37	0.172

Table 2: Percent of families owning each item in 1994

	Treatment	Control
Bike	37%	50%
TV	41%	42%
Stove (without oven)	13%	14%

Figure 4: Distribution of Current Household Size

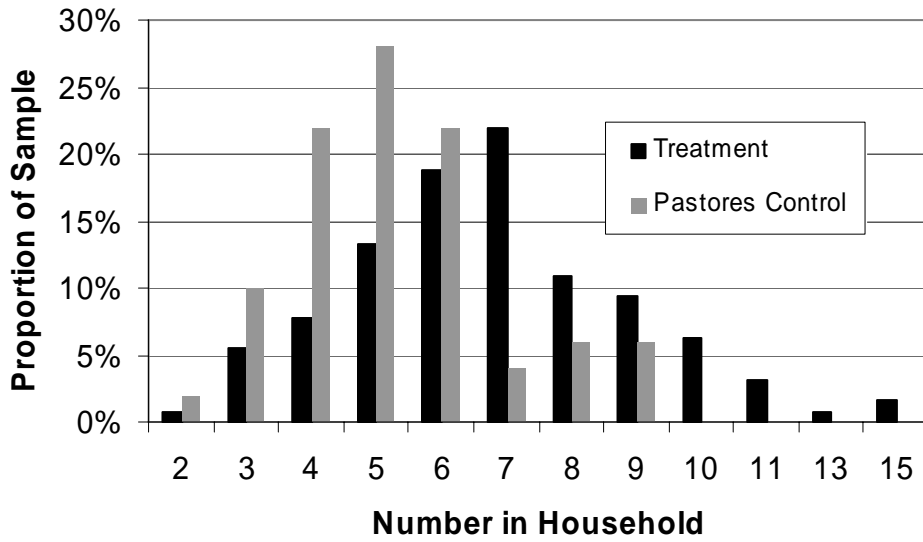
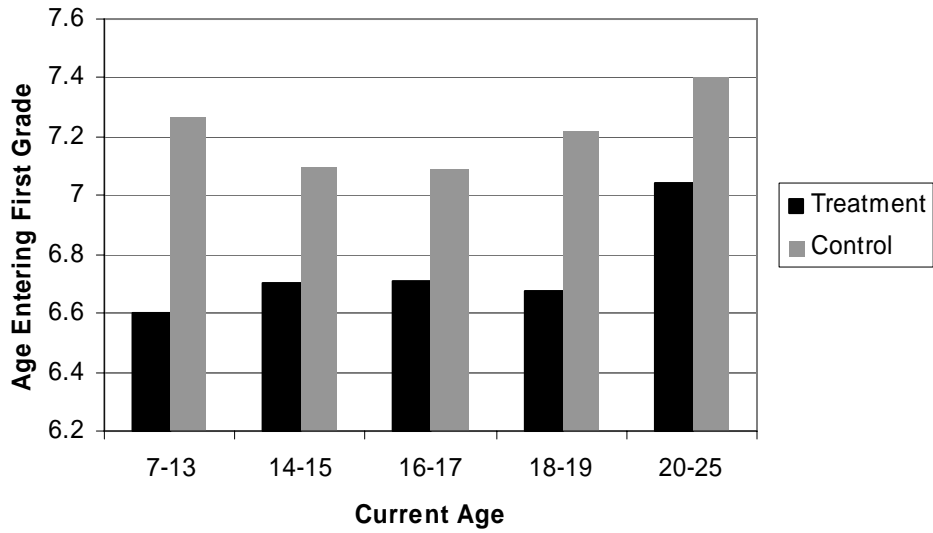


Figure 5: Age Entering First Grade (by current age)



Appendix B

We are interested in the probability that an individual drops out of school in a given year. This event (termination of schooling) will be represented by a discrete random variable Y , where,

$Y_{it}=1$ if the event occurs in year t for individual i

$Y_{it}=0$ if the event does not occur in year t for individual i

and each observation is treated as a single draw from a Bernoulli distribution. The probability of event occurrence, P_{it} , in year t for individual i can be written as a function of the explanatory variables, x_i , and is modeled generally as:

$$P_{it} = \Pr[Y_{it} = 1 | T_i \geq t, x_i] = \Pr[T_i = t | T_i \geq t, x_i] \quad (1)$$

where T_i is a discrete random variable giving the uncensored time of event occurrence (termination of schooling) for individual i , given that the event has not already occurred. P_{it} , known in the duration literature as the hazard rate, falls in the interval from zero to one.

Because Y is observed as a dichotomous variable, we estimate it with a binary choice model based on the method of Maximum Likelihood. Let $\delta=1$ for uncensored observations and $\delta=0$ for censored observations where,

$$\delta_i = \sum_{j=1}^t Y_{ij} \quad (2)$$

Following Allison (1982), the general likelihood function for binary choice, based on the Bernoulli distribution, can be written as:

$$L = \prod_{i=1}^n [\Pr(T_i = t_i)]^{\delta_i} [\Pr(T_i > t_i)]^{1-\delta_i}. \quad (3)$$

An individual's contribution to the likelihood function is determined by whether they have terminated schooling ($\delta=1$, $T_i = t_i$) or not. Allison (1982) notes that the above probabilities can be expressed as a function of the hazard rate P_{it} .

$$\Pr(T_i = t) = P_{it} \prod_{j=1}^{t-1} (1 - P_{ij}) \quad (4)$$

$$\Pr(T_i > t) = \prod_{j=1}^t (1 - P_{ij}). \quad (5)$$

Substituting (4) and (5) into (3) and taking the logarithm, we have

$$\log L = \sum_{i=1}^n \delta_i \log \left[\frac{P_{it_j}}{(1 - P_{it_j})} \right] + \sum_{i=1}^n \sum_{j=1}^{t_j} \log(1 - P_{ij}). \quad (6)$$

Substituting (2) into (6) we are left with:

$$\log L = \sum_{i=1}^n \sum_{j=1}^{t_j} Y_{ij} \log \left[\frac{P_{ij}}{(1 - P_{ij})} \right] + \sum_{i=1}^n \sum_{j=1}^{t_j} \log(1 - P_{ij}) \quad (7)$$

Equation (7) is the log likelihood equation for logistic regression functions. (Allison 1982). We must only choose a functional form for the distribution of the hazard rate, and substitute for P_{it} . Greene (2003) notes that there is little guidance as to which continuous distribution we should choose. Here we use the normal distribution, which gives rise to the following functional form for P_{it} ,

$$P_{it} = \Phi(x_{it}'\beta), \quad (8)$$

and after a bit of manipulation,

$$\ln L(\beta | X) = \sum_{y_{it}=0} \ln[1 - \Phi(X\beta)] + \sum_{y_{it}=1} \ln[\Phi(X\beta)], \quad (9)$$

which is the log likelihood for the probit model.