Making Conditional Cash Transfer Programs More Efficient:

Designing for Maximum Effect of the Conditionality

Alain de Janvry and Elisabeth Sadoulet

University of California at Berkeley

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Abstract

Conditional Cash Transfer (CCT) programs are now extensively used to induce poor parents to increase investment in the human capital of their children. These programs can be large and expensive, motivating the quest for greater efficiency in increasing the impact of the imposed condition on human capital formation. This requires designing the programs' targeting and calibration rules specifically to achieve this result. Using data from the Progresa randomized experiment in Mexico, we show that large efficiency gains can be achieved by taking into account the extent to which the probability of enrollment of a child is affected by a conditional transfer. Rules for targeting and calibration can be made easily implementable by selecting indicators that are simple, observable and verifiable, and that cannot be manipulated by beneficiaries. In the case under study, results show that these efficiency gains can be achieved without rising inequality among the poor.

Alain de Janvry and Elisabeth Sadoulet are professors at the University of California at Berkeley. Their e-mail addresses are alain@are.berkeley.edu, sadoulet@are.berkeley.edu. They are grateful to Harold Alderman, Jean-Louis Arcand, Gabriel Demombynes, Frederico Finan, John Maluccio, Martin Ravallion, K. Subbarao, and Miguel Szekely for their helpful comments.

I. Conditional cash transfer programs and the efficiency question

Conditional cash transfer (CCT) programs targeted at the poor have become widely used, in particular to induce beneficiary households to invest in the human capital of their children. The presumptions of the approach are that the supply side of social services for education and health is in place, and that stimulating demand via income effects is insufficient to induce major changes in human capital investment (Bourguignon, Ferreira, and Leite, 2002). Needed instead is a condition attached to the cash transfer that transforms the income effect into a price effect on the condition. In this case, receiving the transfer requires meeting school attendance and health practice requirements.

The approach has been hailed as a major innovation in how to organize poverty reduction programs. Well known programs that follow this approach include Progresa/Oportunidades in Mexico, Bolsa Escola/Bolsa Familia in Brazil, Red de Protección Social in Nicaragua, Programa de Asistencia Familiar in Honduras, the Program of Advancement Through Health and Education in Jamaica, Food-for-Education in Bangladesh, and Subsidio Unico Familiar in Chile (see Ravallion and Wodon, 2000; Skoufias, 2000; Morley and Coady, 2003; and Rawlings and Rubio, 2005). Some of these programs have become very large and expensive. In 2004, Oportunidades serviced 4 million families at the cost of US$2.2 billion. In 2001, Bolsa Escola covered 4.8 million families at the cost of $700 million. While rigorous evaluations of these programs are still few, positive impacts have been demonstrated for Progresa on education (Shultz, 2004) and health (Gertler, 2004). However, there has been almost no analysis of the effectiveness of alternative program designs in achieving these results, in spite of the large sums spent obtaining them. We address this issue here by analyzing whether better targeting of the qualifying poor and better calibration of the levels of cash transfers could help raise efficiency relative to current levels of achievement.

CCT programs have a double objective: immediate poverty reduction through the transfers, and longer term poverty reduction through the condition to invest in human capital. Meeting the first objective efficiently requires accurate targeting of the transfers on the poor. While targeting cash transfers on the poor is always difficult to achieve (see, e.g., van de Walle, 1998; Alderman, 2001 and 2002; and Ravallion, 2003), we do not address this issue here. Meeting the second objective requires: (1) accurate selection among the poor to minimize the efficiency leakages that occur when payments are made to categories of children already highly likely of going to school without a transfer, as opposed to children who will only go to school because of the transfer; and (2) offering a level of transfer that will secure a high uptake because it is sufficient to meet the opportunity cost of the change in behavior, while minimizing project costs. Specifically, we are concerned with the definition of targeting and calibration rules for CCT programs that can be easily implemented, are cost effective, and transparent. And we are concerned with potential trade-offs between efficiency gains through implementation of these rules and higher inequality in transfers among the poor.

We use Progresa as a case study in exploring these alterative program designs. Results show that efficiency gains in the 29% to 44% range can be achieved over the current scheme and that they are not obtained at the cost of rising inequality among the poor.

II. The efficiency issue in Progresa

2.1. Progresa as a human capital formation program targeted on the poor

In our interpretation, Progresa is a CCT program for human capital formation targeted at the children of the rural poor. It consists in three closely related components for education, health, and nutrition. For education, Progresa offers a monetary grant to each child under 18 years old, conditional on regular school attendance in grades between the third year of primary school and the third year of secondary school and on regular health visits. The health component provides basic health care for all members of the family. The nutritional component includes a monetary transfer conditional on regular visits to a health center, as well as nutritional supplements for children and women in need.

Progresa was introduced in 1997 and, by 2000, had achieved full coverage of marginal rural municipalities, reaching 2.6 million families. The overall budget for that year was US$950 million, of which 44% was for educational grants (Coady, 2000). These transfers benefited approximately 1.6 million children in primary school and 800,000 in secondary school.

The transfers that Progresa families receive result in a significant increase in their income, equal on average to 22%. The targeting of Progresa has explicitly been on poor households living in marginal rural areas of Mexico. Our purpose is not to question this targeting, which corresponds to Progresa's objective of transferring resources to poor families. Our purpose is to explore whether, for a given budget constraint, targeting and calibrating transfers among the poor can help raise efficiency in increasing school participation. We consequently only look at Progresa's educational component, and use it as a laboratory to explore alternative targeting and calibration rules. The idea is to derive lessons from this richly informed experiment that can be applied to Progresa and to other CCT programs where the targeting issue is critical due to severely limited budgets.

To measure its impact, Progresa selected a sample of 506 marginal communities comprising 24,000 households and 17,000 children eligible for transfers, to which a survey was applied a year before the program started and subsequently every 6 months during three years. Information was collected on individual, household, and community characteristics. The sample design consists in the random selection of 320 treatment communities and 186 control communities from among these 506 communities. We restrict our analysis to the children that were in school in October 1997. Indeed, among eligible children, 12 percent had dropped out of school, some for several years, and, while the program has indeed helped bring some of them back to school, this one time effect at the onset of the program is not the focus of our analysis. For most of our analysis, we further restrict the sample to the 2,242 poor children who graduated from primary school in the summer 1998 and were facing the decision of whether or not to continue in secondary school. We use this information to estimate a model of the school enrollment decision that captures, in particular, the impact of Progresa transfers, paying particular attention to heterogeneity of conditions among children. We then simulate alternative targeting and transfer schemes, and compare their efficiency.

2.2. Focusing on entry into secondary school

In this section, we make a simple analysis of the overall Progresa budget to suggest that an efficient scheme for school enrollment should strictly focus on the transition from primary to secondary school, a point already suggested in the IFPRI evaluations (Skoufias, 2000; Coady, 2000; Schultz, 2004).

The conditional transfer offered to each particular child is calculated from the program rules.[1] The program has a schedule of educational grants that increase as children progress to higher grades, and are higher for girls than for boys in secondary school (Table 1). There is, however, a maximum amount to the total conditional transfer that can be offered to each household, set at $625/year in 1998 (including the $100 granted for nutrition).[2] In the sample, 13.4% of eligible children are affected by the household transfer cap rule. Using the proportionality rule that Progresa applies, we calculate the conditional transfer to which a child can pretend by scaling down by the same factor all the school grants in any household that would surpass the cap.[3] Among the children graduating from primary school, 28% are affected by the cap, and the conditional transfers offered vary from $100 to the full $200/210, with an average value of $169. Using these conditional transfers and the enrollment status of each child gives the budget for educational grants in the treatment communities from the sample as reported in Table 1, with its distribution by grade. Overall, the budgetary saving implied by the cap put on the total household conditional transfer represents 17% of the budget with no cap. Taking into account these caps, primary school accounts for 55.4% of the total educational budget and the first year of secondary school for almost 20% (Table 1).

Other studies have shown that Progresa's conditional transfers do increase continuation rates at all grades (Behrman et al., 2001; de Janvry et al., 2001; Shultz, 2004). However, as shown in Figure 1, school continuation rates are very high in primary school and again in secondary school. Because of these high continuation rates in primary and secondary school, the gain obtained from the conditional transfers is only of around one percentage point in primary school grades, and one half of one percentage point in the 2nd and 3rd years of secondary school. This suggests that the current CCT scheme is unnecessarily expensive for primary school grades from an efficiency standpoint. Indeed, while the conditional transfer to a primary school child is approximately $100/year ($10 per month over 10 months), 96 school-attending

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[1] We call "conditional transfer" the exogenous amount that a child would receive from Progresa if he is in a treatment community and attends school. This conditional transfer depends on the gender and grade of the child and the household's demographics. At the level of the household, the conditional transfer is the total amount that the household would receive if it were in a program community and complies with all Progresa rules.

[2] This cap was introduced so the program does not induce a fertility response.

[3] For households affected by the cap, all conditional transfers are scaled down by a common factor so they add up to the cap. This prevents these households from keeping any child out of school without penalty.

children are paid for each child that is retained in school by the conditional transfer incentive, implying that the effective cost per additional child attending primary school is $9,600. Assisting the 3-4% of children that drop out of school at each grade would require a very different program. Eliminating all transfers to primary school students would in itself save 55.4% of the educational grant budget, or $230 million out of the total budget of $950 million in 2000.

The critical problem in terms of educational achievement occurs at entry into lower secondary school. We, therefore, continue our analysis of the CCT program only for secondary school.

2.3. The efficiency issue with Progresa's educational grants

There are two sources of inefficiency in a CCT program that need to be optimally reduced:

The first is paying people for what they do anyway. As we have seen, this is obvious in primary school. But the problem also arises in secondary school: 64% of the poor children that graduate from primary school would enter secondary school without a conditional transfer. Reducing this efficiency leakage requires being able to anticipate who might not be going to school. Hence, we rely on the ability to predict the probability that a given type of child will enroll in school. Because such a prediction is necessarily noisy, there is no possibility of completely avoiding this inefficiency.[4] The question, however, is to reduce it by not targeting children most likely to go to school anyway.

The second source of inefficiency comes from offering incentives that are either too high or too low relative to the minimum amount needed to induce the conditional action. As we will see later (Table 2, column 1), the simple difference estimation of the impact of Progresa indicates that the program has raised the enrollment rate from 63.6% to 76.6%. The conditional transfers offered were thus sufficient for the 13% that were attracted to enroll in secondary school and would not have done so otherwise. With them, could we have done as well with a smaller conditional transfer? For the 23.4% that did not take up the conditional transfer offered, the grant was not sufficient. Would they have taken the offer had it been at a

[4] This inefficiency concept is analogous to the issue of fungibility with infra-marginal transfers, whereby beneficiaries substitute other consumption for those subsidized by the program, meaning that the program has no real effect on total consumption of the targeted commodity.

higher level and, if so, should the conditional transfer offered to them be increased if we can identify who they are?

If there were a clear opportunity cost to children's time in school, one could calibrate the subsidy to match this level. This is the underlying reasoning for the calculation of the Progresa CCT. It represents 40% of what children of comparative age earn when they work. However, children's opportunity cost of time at school is not easy to establish. Less than 30% of the children that drop out at the end of primary school work during the subsequent 18 months (45% for boys and 10% for girls), increasing to 35% (55% for boys and 12% for girls) the following year. Among the reasons given for not continuing school, lack of money or need to work come first with 57% of the answers, but other important reasons are given such as the child does not like school or does not learn (23%) and the school is too far (13%). What needs to be known is the response function of children to incentives in order to maximize the return to conditional transfers. This is what the Progresa randomized experiment allows us to do. Since there was no experimentation to observe the response to different levels of conditional transfers, we exploit the particular feature of the cap on total conditional transfer to a household to infer the marginal response to varying conditional transfer amounts.

Dealing with these two sources of inefficiency requires an accurate predictive model of the probability of going to school as a function of the characteristics of the child, the household, and the community and of the conditional transfer amount offered. We concentrate our analysis on entry into secondary school since this is where the conditional transfer can induce an important change in behavior resulting in efficiency gains.

We do not question the conditional transfers offered to children in 2^{d} and 3rd grades of secondary school for two reasons. First, anticipation of these conditional transfers is part of the expected benefits from entering secondary school, and the measured impact of the current Program thus includes their effect. Second, while we observed very high continuation rates in secondary school, these observations are made on the selected group of children that voluntarily entered secondary school without any subsidy. Other children that are induced to enter secondary school with a conditional transfer are very unlikely to continue at the same rate into the following grades if the subsidies were discontinued. We have no experimental design that allows us to study this particular continuation rate since Progresa always supported the first three grades of secondary school. The safe bet is that, whatever support is provided for the first grade needs to be provided for all three grades of secondary school, as it is currently. And while there are many less children in the second and third grades of secondary school than in the first grade among Progresa children in 1998, because it is the first year of the program, these numbers should even up after three years of program implementation. We will thus apply the results of our analysis for the first grade to all three grades of secondary school.

III. A model of optimal cash transfer

3.1. The optimal variable CCT scheme

Denote by $P(X,T)$ the probability that a child with characteristics *X* and eligible for a conditional transfer T will enroll in school. Eligibility is denoted by the index function $I \in [0,1]$. Children characteristics are distributed according to the density function $f(X)$.

The allocation problem consists in choosing the eligibility status $I(X)$ and, if eligible, the conditional transfer $T(X)$ offered to a child with characteristics *X*, to maximize the gain in enrollment over the population:

$$\max_{I(X),T(X)} \int \left[P(X,T) - P(X,0)\right] I\, f(X)dX\,, \tag{1}$$

subject to a budget constraint:

$$\int P(X,T)T\, I\, f(X)dX \le B\,, \tag{2}$$

where B is the budget available for the program. The first order condition for the optimal conditional transfer is that, for any eligible child $(I = 1)$,

$$P_T - \lambda(P_T T + P) = 0\,, \tag{3}$$

where $P_T = \dfrac{\partial P}{\partial T}$ and λ is the Lagrange multiplier associated with the budget constraint. This relationship states that the ratio of cost $(P_T T + P)dT$ to enrollment benefit $P_T\, dT$ of a marginal increase dT in the conditional transfer offered is equal across children. Hence, the cost of the marginal child brought to school is equal across children types *X*. Note that the cost has two terms. The first term $P_T TdT$ is the transfer cost to the marginal children $P_T\,dT$ brought to school by the increase in conditional transfer. The second term is the cost of giving the increase in transfer dT to all P children of the same type X, even though they went to school with the initial T. This is the marginal equivalent of the decomposition of the cost of transfers:

$$P(X,T)T = [P(X,T) - P(X,0)]T + P(X,0)T \ ,$$

where the first term represents the cost of the transfers to the kids brought to school by the conditional transfer, and the second term the cost to the kids of similar observable characteristics who would have gone to school anyway.

Given the optimal conditional transfer amount conditional on eligibility, the optimal eligibility rule is defined by:

$$I = 1 \ \text{ if } \left(P(X,T) - P(X,0)\right) - \lambda P(X,T)T \geq 0 \ \text{, 0 otherwise .} \tag{4}$$

The optimal allocation of a budget B is thus the solution to the system of equations (3), (4), and (2).

In the particular case of a linear probability model that we consider in the following empirical work, the conditional expectation of the enrollment probability is written:

$$EP(X,T) = X\beta + \delta_0\, I + X\delta T \ , \tag{5}$$

where $\delta_0\, I + X\delta T$ measures the total impact of T, and $X\delta$, which includes a constant term, measures the marginal impact of T. The presence of an intercept $\delta_0\, I$ is motivated by the fact that we only observe conditional transfers in the range \$100 – \$210, and thus cannot impose the linearity of the CCT effect to extend below that range to a 0 conditional transfer.

The optimal conditional transfer and eligibility criteria defined in equations (3) and (4) are written:

$$T = \max\left(\frac{1}{2\lambda} - \frac{1}{2}\frac{X\beta + \delta_0}{X\delta}, 0\right), \tag{6}$$

where λ is solution to the budget constraint (2). This expression shows that both eligibility and the optimal conditional transfer for any given child are function of the ratio $\frac{X\beta + \delta_0}{X\delta} = \frac{EP(X,0) + \delta_0}{EP_T}$. The first term in the numerator is the expected probability that children with characteristics X would go to school even without a conditional transfer, and the denominator is the marginal effect of the conditional transfer on the expected enrollment probability. Children will thus be eligible and be offered high conditional transfers if they have a low initial probability of enrollment and/or a high enrollment response to a conditional transfer. This optimal conditional transfer is function of all the characteristics X that predict enrollment, albeit in a very non-linear form. Whether any program can use such a complex formula to compute conditional transfers is questionable. Yet, it is a useful benchmark, as it gives the maximum efficiency that could be reached with the observables X, and we will thus compute it in the empirical analysis that follows. We, however, turn next to the definition of the optimal scheme constrained to be linear and to use a small number of observable characteristics.

3.2. An implementable CCT scheme

To be useful for program implementation, eligibility rules need to be simple and transparent. Indicators used to determine eligibility and the level of conditional transfers must be few, easily observable and verifiable, and non-manipulatable by households. Simplicity and transparency are also important to ensure the political acceptability of a subsidy program (Schady, 2002). Progresa uses grade and gender to set the schedule of conditional transfers (Table 1). The objective is thus to simplify the formula (6) established for the optimal CCT scheme to a linear index based on a few characteristics Z of the children.

The allocation problem consists in choosing the eligibility status and, if eligible, the conditional transfer to offer to each child to maximize the gain in enrollment over the population (1), subject to a budget constraint (2), and using simple linear formulas for eligibility and conditional transfer:

$$T = Z\alpha,$$

and $$I = 1[Z\gamma \geq \gamma_{\min}],$$

where Z is a subset of characteristics of the children, and α, γ, and $\gamma_{\min}$ are parameters to be determined. As in the model above, optimal eligibility is defined by the sign of the optimal conditional transfer value:

$$I = 1 \quad \Leftrightarrow \quad T = \max(Z\alpha, 0) > 0. \tag{7}$$

The parameters α are solution to the maximization of a quadratic function:

$$\max_{\alpha} \sum_{i \in E} m_i Z_i \alpha - \lambda \left[B - \sum_{i \in E} \left(P_{0i} + \delta_0 + m_i Z_i \alpha \right) Z_i \alpha \right], \tag{8}$$

where E is the set of eligible children, $m_i = X_i \delta$ is the marginal effect of the conditional transfer on child i school enrollment, $P_{0i} = X_i \beta$ is its enrollment probability without conditional transfer, and λ is the Lagrange multiplier on the budget constraint. The conditional transfer formula (7) is, therefore, a simple linear combination of a few observed characteristics Z. It is similar to the scoring system used in many welfare programs, whereby characteristics Z command scores α that add up to an aggregate score $Z\alpha$. In this case, $Z\alpha$ determines not only eligibility but also the conditional transfer amount. An important empirical question is whether the use of this simple scoring scheme is sufficiently close to the optimal CCT scheme, and what type I (exclusion) and II (inclusion) errors are made in this implementation. We will return to this question after we establish these schemes.

IV. Predicting enrollment

We now proceed to build a predictive model of entry into secondary school. Although a probit and a logit perform better at high and low probabilities, we use a linear model to avoid imposing heterogeneity on the impact of the conditional transfer through the functional form, since this will be an important determinant of the targeting scheme.[5] We use the sample of children finishing primary school and eligible for a Progresa CCT (defined as poor using the Progresa welfare index) in both the control and treatment communities. Randomization in the selection of communities insures that being in a treated community is orthogonal to the characteristics of the children.[6] The average treatment effect can thus be obtained by simple comparison of the average enrollment of children in the two types of communities. The actual amount of conditional transfer offered to a child is, however, not orthogonal to its characteristics. This is because, being subject to the cap rule and to the corresponding household scaling factor are both function of the children's age structure, which is likely correlated with household preferences that influence

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[5] In the simulation exercises that follow, we will never encounter a problem of predicted negative probability (the majority of children have predicted probabilities above .40), but we do have some predictions above 1, even without conditional transfer and more when applying conditional transfers. For simulation purposes these will be set equal to 1.

[6] The quality of the randomization is verified and documented in Behrman and Todd (1999).

schooling decisions. The impact of the continuous treatment effect is thus estimated controlling for the conditional transfer level.

The empirical equivalent to equation (5) is written as:

$S_i = \delta_0 I_v + \delta I_v T_i + \beta_0 T_i + u_i$,

or $S_i = \delta_0 I_v + \delta I_v T_i + \beta_0 T_i + X_i \beta + u_i$, with control variables X_i .

In these equations, S_i is a binary variable indicating the enrollment status of child i, I_v is a dummy variable that indicates whether i lives in a treatment community, and T_i is the conditional transfer that i is eligible for under the program. The control variables X_i are child, household, and community characteristics.

Table 2 reports the estimation results for different specifications and Table 3 gives the corresponding marginal effects for particular types of children. The result in column (1), Table 2, gives the simple difference effect of the Progresa CCT (variable I_v) on enrollment. Among qualifying poor, the impact of the program on the probability of continuation into secondary school is 13%. As expected, this is slightly higher than the 8-9 percentage points estimate of impact on enrollment conditional on completed primary school (i.e., including children who had dropped out of school prior to the onset of the program) obtained in other studies (e.g., Schultz, 2004).

Using, in column (2), the value of the conditional transfer (variable $I_v T_i$), which varies across children due to the cap on household transfer that affects 26% of the qualifying children, we see that the marginal effect of a dollar of conditional transfer is high (1.42% per 10 dollars). Note that the imposed linear form gives a meaningful positive effect only for conditional transfers above $100, which is not really restrictive as current conditional transfers are much higher. Adding a large number of child, household, and community controls in column (3), indicates that the main correlates of a child's secondary school enrollment are age of the child (negative), mother's literacy and the household's maximum educational level (positive), the number of agricultural workers and self-employed in the household (negative), total expenditure (positive), and distance to school (negative). State effects are also important. Both models predict that the current US$200 conditional transfer increases the probability of enrollment by the same 14% (Table 3), which confirms that controls are orthogonal to the treatment.[7]

We then proceed in columns (4) and (5) to explore heterogeneity of impact across categories of children without and with controls, respectively. We focus on aspects of heterogeneity that may be useable for targeting purposes. They are age of the child[8], father's ethnicity, and whether there is or not a secondary school in the community. Progresa recognizes gender differences, which we do not find to be important in explaining differential impacts of transfers on the decision to continue into secondary school.[9] We see from the results that age, ethnicity, and presence of a school in the community all make large differences on enrollment, both directly as controls, and in affecting the impact of the conditional transfer. We use the results in column (5) as the predictive model to evaluate the impact of targeting on enrollment.

Heterogeneity implies large differences in the impact of a conditional transfer on enrollment across categories of children (Table 3). For a 12 years old male child, with a non-indigenous father, and a school in the community, the $200 conditional transfer only increases the probability of enrollment by 3–4%. If this child is two years behind normal progress, the conditional transfer increases the probability of enrollment by 10–12%. When this child has an indigenous father or no secondary school in the community, the conditional transfer increases enrollment by 9–11%. Combining the features of being a boy, 14 years old, with an indigenous father, and in a community with no secondary school, indicates that a $200 conditional transfer raises the probability of school enrollment by 23–24%. These large differences suggest that there can be efficiency gains in using some of these dimensions of heterogeneity for the

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7 Another interesting result in column (3) is the relative magnitude of the impacts of a conditional transfer (I_v variable) vs. a non-conditional transfer (household total expenditure variable) on enrollment. While the result is only suggestive because total expenditure is endogenous, the $200 conditional transfer increases the probability of enrollment 17 times more than an equal non-conditional transfer.

8 The age is centered on 12 years old, where 12 is the median age for entry into secondary school, so that the coefficient on the direct variable is readily readable as the impact on a 12 years old.

9 The lack of significance and very low point estimate (0.003 with standard error 0.002) are robust to many specifications, including either less or more interactions terms, and introduction of a number of control variables. We, therefore, drop the term from the estimation in column (5) that will serve for the simulations. The often reported difference between boys and girls comes from estimations of enrollment rather than continuation rates. Coady (2000) shows that most of that difference comes from the very high impact of Progresa on re-entry of girls into the school system the first year of the program.

targeting of conditional transfers, in the same way as Progresa used gender differences in setting conditional transfer levels.

A potential concern is that identification of the impact of the size of a conditional transfer on enrollment derives from observation of children who are offered less than the full grant due to the cap on total household conditional transfers. These children are, by definition, from households with a larger number of eligible children. To check that the enrollment model for these households does not differ in any significant way from that for smaller households, we compare our estimation with a model estimated for these children alone. The estimation is, as expected, more precise with the whole sample, but the parameters are neither individually nor globally significantly different in the two estimations (the p-values for the test of equality of the parameters on the conditional transfer variables are 0.49 without heterogeneity and 0.16 with heterogeneity), which confirms that identification of the conditional transfer parameter is correct. We also checked the orthogonality of the conditional transfer to all other variables by estimating different models for children in the treatment and control communities, and verify that the parameters are neither individually nor globally significantly different in the two estimations. Hence, the model that we have estimated can be used for predicting behavior in absence of a CCT program.

V. Comparing alternative CCT schemes

We now proceed to analyze, in Table 4, three alternative targeting and calibration schemes with the purpose of seeing if they can help raise the efficiency of conditional transfers in inducing school enrollment. The different schemes all add up to the same total budget spent in implementing the current Progresa CCTs. This budget is computed by predicting for each sample child the expected uptake (predicted probability) $\hat{E}P$, and summing up expected transfers $\hat{E}P.T$ over the children. It amounts to a total annual outlay of $322,000 for the 2,242 sample children.[10] In the upper panel, we report the

[10] Another interesting exercise would be to define an efficient allocation of the total educational budget of the current Progresa program. It would consist in reallocating the primary school budget to secondary school, thus doubling the budget for secondary school. A simulation of this budget re-allocation shows that it would lead to almost universal secondary education with enrollment rates between 90.4% and 91.7% depending on the rule used for transfer calibration.

enrollment rates for all children, and then by category of children according to their "risk level", i.e., their predicted enrollment rates without any conditional transfer, or their eligibility status in the program. In the lower panel, we report some aggregate targeting and cost outcomes for the different schemes.

5.1. Emulating Progresa: a universal uniform CCT scheme

The school participation rate without conditional transfer is 63.2% (Table 4, col. (1)). Progresa's current universal CCTs with a cap and with differential values for boys and girls, raise the participation rate to 75.7%, a gain of 12.5 percentage points. The universal uniform CCT scheme without a cap and without gender differences that we use as a benchmark for the subsequent simulations raises participation to an identical 75.7% (col. (2)). Under this scheme, the conditional transfer per child is \$194/year.[11] Because many children receive a transfer even though they would be going to school without one, the cost per additional child enrolled is \$1,151/year.

Figure 2 shows the enrollment probability with this CCT program according to the initial enrollment probability without a CCT program. The distance from the diagonal to the curve thus represents the gain in enrollment from the program. Gains are largest for children with a low probability of enrollment and they decline as the enrollment probability rises. Table 4 reports these gains, with enrollment probability rising from an average 27.8% to 47.2%, or 19.4 percentage points, for the children with probability of enrollment lower than 40%, while the gain is only 5.6 percentage points for those in the 80-100% category (Table 4, cols. (1) and (2)). Gains are hence progressive in terms of the initial likelihood of going to school, even with a uniform CCT scheme. This is the Progresa achievement that has been widely acclaimed in the literature. However, can we do better by redefining the targeting and the calibration of conditional transfers?

5.2. An optimal variable CCT scheme

The second scheme implements the optimal variable CCT scheme established in the model, under the same budget constraint and taking into account heterogeneity in probability of enrollment and responses

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[11] The conditional transfer level is determined to match the Progresa budget, taking into account the predicted uptake that it induces.

to transfers across children. Both eligibility and the optimal conditional transfer value are simultaneously determined. This is done by offering the conditional transfer defined in (6) to children of characteristics *X*. To compute the conditional transfer values, we use the estimated values for β, δ_0, and δ reported in Table 2, column 5, and find by tâtonnement the shadow value λ of the budget constraint that balances the budget. The resulting conditional transfers vary from $100 to $350, depending on the child's characteristics. Under this scheme, we raise the conditional transfers to children with a low probability of going to school, and target less the children with high probabilities of going to school because efficiency leakages are particularly high among them. Using again the best predictor model for enrollment (Table 2, column 5), we predict enrollment for every child in the sample. Results in Table 4 (col. (3)) show that students eligible to receive a conditional transfer have an average probability of enrollment of 78.9%, compared to 55.8% had they not been offered the conditional transfer. The non-eligible students have an average probability of enrollment of 89%. Overall, the probability of school enrollment is now 81.1%, an efficiency gain of 43.6% over the universal uniform CCT scheme. As can be seen in Figure 2, this optimal CCT scheme almost equalizes enrollment rates among children with initially very different enrollment rates to values close to 70%. The largest gains in probability of enrollment are thus captured by those with the lowest initial probabilities.

Figures 3 illustrates the optimal CCT scheme. It shows the distribution of children by initial enrollment probability without a CCT program, superimposing the distribution of those that are eligible in the optimal scheme (in black), and showing, by difference, the distribution of non-eligible (in grey). It clearly shows how eligibility is concentrated on the children with low initial probabilities, while the non-eligible all have initial probabilities above 0.70. The optimal calibration of conditional transfers also favors those with low initial probabilities, trying to induce them to go to school with higher conditional transfer. The conditional transfers decline as the probability of going to school without a transfer rises. As can be seen in Figure 3, there are, however, relatively few children with predicted low enrollment probability: the majority of them is concentrated in the 40-80% enrollment rate range.

Returning to Table 4, we see that 77.5% of the children are eligible for a conditional transfer. The average conditional transfer is $237 compared to the universal uniform conditional transfer of $194, a 22% increase. The optimal scheme thus suggests raising conditional transfers for the beneficiaries while reducing coverage over those with high likelihood of going to school without a conditional transfer. Since there are still efficiency leakages among eligible children, the cost per additional child enrolled is $802, down from $1,151 under the universal uniform CCT scheme. Cost saving per additional child enrolled is thus no less than 30%.

5.3. An implementable CCT scheme

Having established the optimal CCT scheme as an efficiency benchmark, we now turn to the definition of simpler implementable CCT schemes, based on a linear combination of a few observable characteristics. For a given set of variables *Z*, the implementable scheme is the solution to the optimization problem defined in (7) and (8). The values for β, δ_0, and δ are taken from the enrollment model (Table 2, column 5), and we solve for the parameters α and λ iteratively.[12] We explore combinations of characteristics *Z* that correspond to the criteria of being easily observable, verifiable by others, and non-manipulatable by the household. An efficiency criterion for selection consists in choosing characteristics that are important correlates of enrollment (so as to focus targeting on the children least likely to enroll without a conditional transfer) or indicate high sensitivity of enrollment to a conditional transfer. In addition to these features, actual implementation of a program requires these criteria to be legally and politically acceptable. This is clearly an issue that every program would have to address in its own particular context.

In our base model, we restrict the CCT scheme to only depend on gender and birth order of the child, presence of a secondary school in the community, distance to a secondary school if there is not one in the community, and state dummy variables, which are all strong correlates of enrollment. We later report a few alternative specifications. Note that age of the child is not used since an eligibility criterion based on age could induce perverse behavior, with parents delaying their children's entry in secondary school to benefit from a larger conditional transfer. The rank of the child in the family, which cannot be

[12] Starting with general eligibility, we solve the optimization problem (8) for α as a function of λ and adjust λ to balance the budget. These parameters are used to compute transfers and define eligibility. We iterate this procedure until there is convergence, i.e., no change in eligibility between two consecutive iterations. This is always achieved in less than 5 iterations.

manipulated, turns out to capture part of this information. Every single one of these variables can be easily observed and verified. In fact, instead of secret eligibility formulas as currently used for poverty that give little room for recourse and accountability, self-registration is possible, with easy verification. The results are reported in the first panel of Table 5, column (1). The birth order parameter indicates that the conditional transfer is highest for the oldest child and decreases by $12 for each of the younger siblings. Girls would optimally receive a premium of $25. The main source of variation in conditional transfer is, however, related to distance to school, with a large premium given to children that need to travel to school and an additional amount for each kilometer traveled. The scheme also exhibits some variation across states, with a difference of $87 between the extreme cases of Queretaro and Guerrero.

Examples of eligibility and conditional transfer amounts computed with this simple points system are reported in the lower panel of Table 5. Children with a school in their own community are not eligible; they represent 23% of the sample. Their enrollment rate without conditional transfer is predicted at 80.5%, which is also the rate observed in control communities with a school. By contrast, all the children who do not have a school in their community are eligible for some conditional transfer.[13] A boy, oldest child, and living 3kms away from a school (which is the mean value among those without a school in their community) would be offered a conditional transfer of $213, while the offer to the third child would only be $190. If the oldest child is a girl, she is offered $239. Cumulating all the disadvantages, a girl living 6kms away from school would be offered the highest transfer at $266.

Implementation of this CCT scheme results in enrollment rates and efficiency levels reported in column (4) of Table 4. There is of course an efficiency loss relative to the optimal CCT scheme, the cost to be paid for simplicity and transparency. Although the number of eligible children is about the same as in the optimal CCT scheme (77.4%), the eligibility criterion is not the same. The implementable scheme includes 9% of the children not eligible under the optimal scheme (type II error) and exclude 9% of the children eligible under the optimal scheme (type I error). Enrollment of eligible children rises from 58.2% without a conditional transfer to 79.1% with one. The enrollment rate for the non-eligible is 80.5% and for

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[13] The average distance to school for the 77% children that do not have a school in their community is 3.1 kms, Enrollment rates are observed to decrease very sharply with distance to school in the control communities, reaching the low value of 43% for the 19% children living further away than 4kms.

the population of poor is 79.4% overall. This implies a 29.4% efficiency gain over the universal uniform CCT scheme. Cost per additional child enrolled is $889, still 23% cheaper than under the universal uniform CCT scheme, but 11% more expensive than under the optimal scheme.

We explore alternative implementable schemes, varying the characteristics used to establish eligibility and conditional transfer amounts (Table 5). Adding mother and father illiteracy (column (2)), which are important predictors of school enrollment, raises the efficiency gain to 31% above the universal uniform CCT. While some would argue that such subsidies (here computed as $26 and $30 if the mother or the father are illiterate, respectively) may give the wrong signal and bias the return to education, one can also see them as a way of compensating for the handicap that children of uneducated parents have and of helping them catch-up. At the other extreme, one can ask how efficient would it be to define CCT schemes at the community level (although only for the poor). This is reported in column (3) of Table 5, and shows an important efficiency gain of 28.5% over the uniform CCT scheme. This geographical targeting scheme is interesting, as it shows that in the particular case of rural Mexico, an important efficiency gain could be obtained by redesigning the CCT program as a school transportation subsidy. This simple transportation subsidy would capture 65% of the efficiency gain that the optimal CCT scheme would garner. The question arises then of comparing this intervention with a supply-side policy that would bring schools closer to where people live. This is beyond the scope of this paper, but Coady (2000) estimated that the cost of raising enrollment through a supply-side intervention that increases the number of rural schools would be more than seven times as much as the current Progresa program.

These specific implementable schemes are illustrations of the idea that designing a relatively simple CCT scheme, with a points system that is transparent and easily verifiable, is indeed feasible and could ensure large efficiency gains.

5.4. Comparing direct costs and efficiency leakages under the three schemes

An important determinant of the relative efficiency of different targeting schemes is the importance of their efficiency leakages, namely the magnitude of the transfers that go to children that would go to school without the conditional transfer. This is analyzed in a comparative fashion in Figure 4 where the total transfer cost for each category of children is divided into direct costs (transfers to children that would not otherwise have enrolled, represented in black) and efficiency leakage costs (transfers to children that would have enrolled anyway, represented with stripes). Differences among the figures are quite telling.

With the universal uniform CCT program (Figure 4a), leakages are particularly high, especially among children with a high probability of going to school without a conditional transfer. Altogether, 83.2% of the total budget goes to efficiency leakages, leaving an effective direct cost of only 16.8%. The optimal variable CCT program reduces efficiency leakages by focusing eligibility among low probability children and increasing the magnitude of the conditional cash transfers offered to them (Figure 4b). Efficiency leakages are reduced to 64.9%, implying an effective direct cost of 36.1%. The implementable CCT program has an efficiency leakage of 72.5% (figure not reported). Because targeting is simplified and transparent, it is a compromise between the universal and the optimal CCT schemes. Its effective direct cost is 27.5%.

We conclude that the optimal variable CCT scheme could offer a significant efficiency gain in school enrollment. It could be implemented through a secret formula as Progresa currently uses to target poverty. This may, however, be too complex to administer, and secrecy is not a desirable feature to allow recourse. However, results show that the implementable variable CCT scheme with transparent targeting also results in substantial efficiency gains relative to Progresa's current universal uniform conditional transfers.

VI. Efficient CCT schemes and equity

Are these optimal and implementable schemes regressive or progressive among the poor? In other words, are efficiency gains in enrollment achieved at an equity cost? Conditional transfers driven by efficiency gains indeed raise the issue that maximally efficient schemes may be inequitable (Das, Do, and Özler, 2005). For this reason, eligibility is restricted to the poor. However, when there is further targeting among the poor, are the resulting transfers regressive or progressive on them?

Before looking at the distributive effect of this targeting among the poor, it is interesting to note that the Progresa transfers themselves were not particularly efficient to reduce poverty or inequality. Indeed, when measuring poverty by consumption per capita, the per capita transfers were almost uniformly distributed across levels of per capita consumption (de Janvry and Sadoulet, 2003). In this paper, we discuss the issue of trade-off between efficiency and equity using the Progresa welfare index measured in 1997, rather than the income/consumption level, since this is what Progresa uses as a poverty indicator. We illustrate in Figure 5 the average distributed transfer with households ranked by the Progresa welfare index. The average transfer distributed by Progresa shows a clear upward trend and thus regressivity among the poor. This is due to the low uptake rate in low welfare classes. By contrast, the average distributed transfer decreases across welfare levels in the optimal CCT scheme (from $160 to $140), and is uniform in the implementable CCT scheme. Efficiency gains in implementing CCT programs designed to maximize the effect of the conditionality are thus not achieved at the cost of rising inequality among the poor.

VII. Conclusions

We raised in this paper the question of whether efficiency gains can be achieved in CCT programs by improved targeting among the poor and better calibration of conditional transfers. The efficiency objective is to maximize impact over the population of the condition imposed on the transfer, in this case gains in school enrollment among the children of the poor. Using the data from the Progresa randomized experiment, we focused our analysis on the crucial educational decision for children in poor Mexican rural communities, namely whether to continue schooling at the secondary level or not.

Achieving efficiency gains through the targeting and calibration of conditional transfers requires focusing on children with a high probability of not going to school without a conditional transfer and with a high response to the amount offered, within the overall program budget constraint. Implementing this program requires predicting school enrollment as a function of the conditional transfer offered and of the child, household, and community characteristics. Heterogeneity in responses shows that age, ethnicity, and presence of a school in the community make large differences on enrollment. We then compared three alternative targeting and calibration schemes: the current Progresa scheme of universal uniform conditional transfers, an optimal scheme of variable conditional transfers, and a scheme of implementable conditional transfers where the criteria used for targeting and calibration are easily observable, verifiable by others, and non-manipulatable by the household. In setting up new programs, a pilot experiment would need to be used to estimate the enrollment probability model necessary to establish the targeting and calibration formulas.

Results show that the optimal scheme gives a 44% efficiency gain over the universal CCT scheme, and the implementable scheme a 29% gain. The optimal scheme reduces efficiency leakages (receipt of transfers by children who would go to school without a conditional transfer) from 83% to 65%, and the implementable scheme to 73%. We also show that these efficiency gains are not achieved at the cost of rising inequality among the poor.

The overall conclusion is thus that large efficiency gains can be achieved in implementing what are in many countries highly expensive CCT programs for human capital formation among the poor if rules for the targeting and calibration of conditional transfers are designed to maximize the effect of the conditionality.

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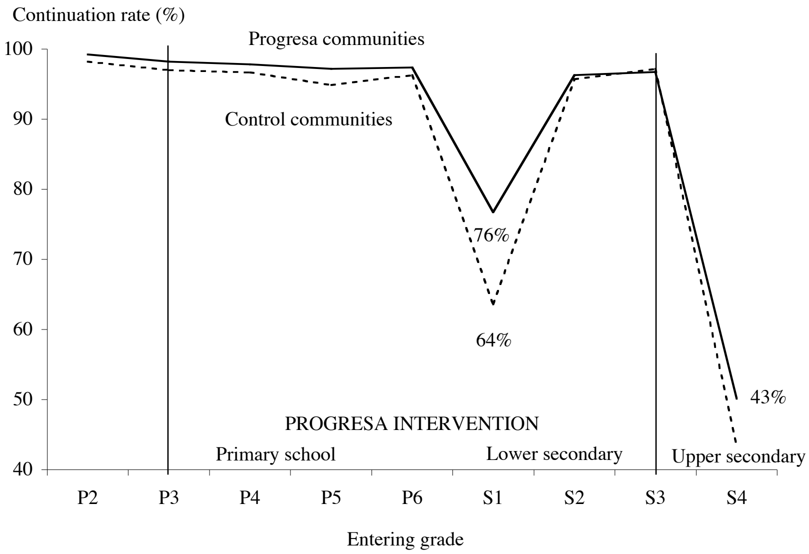


Figure 1. School continuation rates of poor children in sample communities

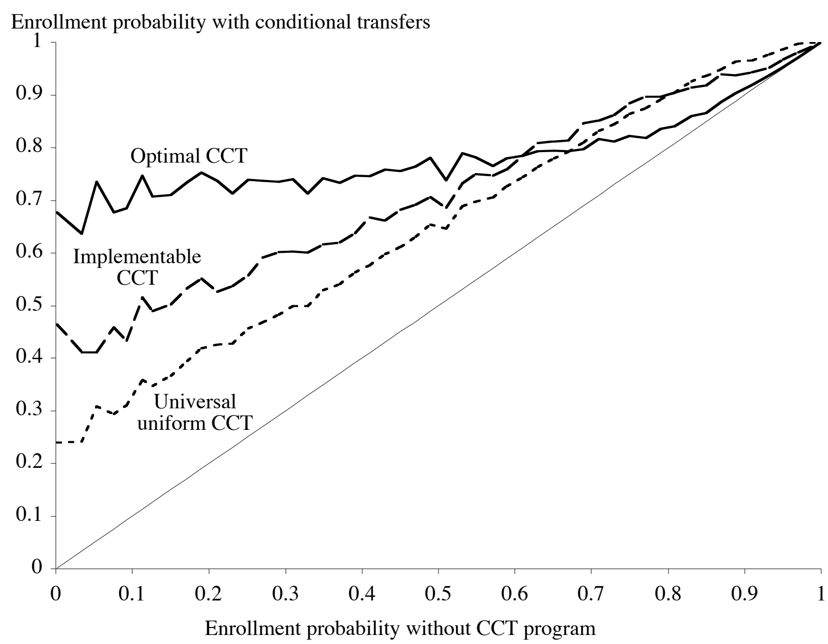


Figure 2. Impact of alternative CCT programs on enrollment rates

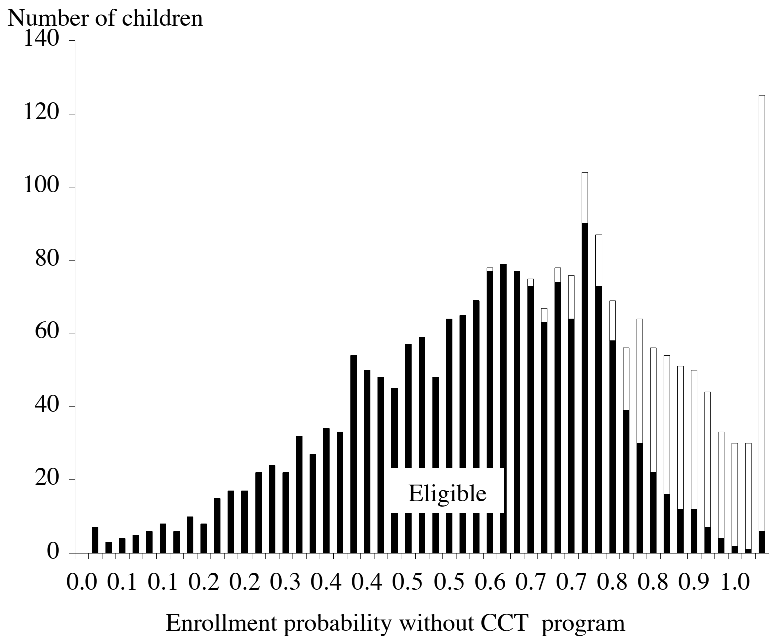
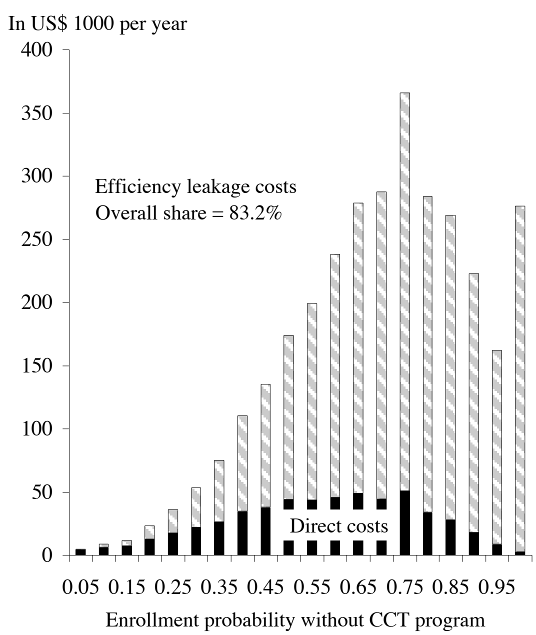
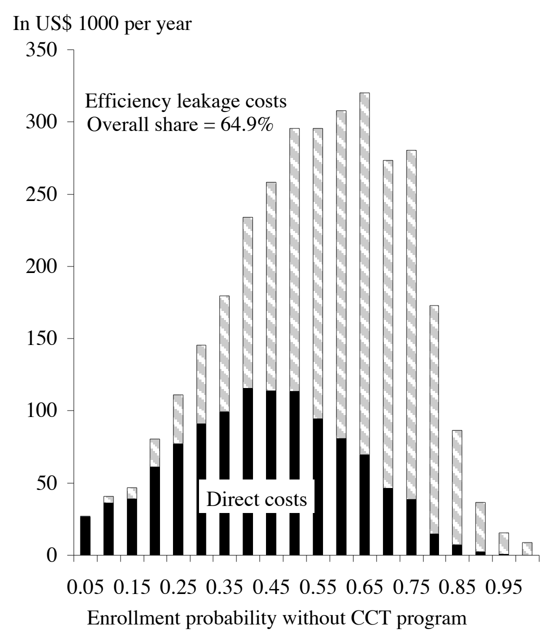


Figure 3. Eligibility in the optimal CCT scheme



4a. Universal uniform CCT scheme



4b. Optimal variable CCT scheme

Figure 4. Total direct and leakage costs under different CCT schemes

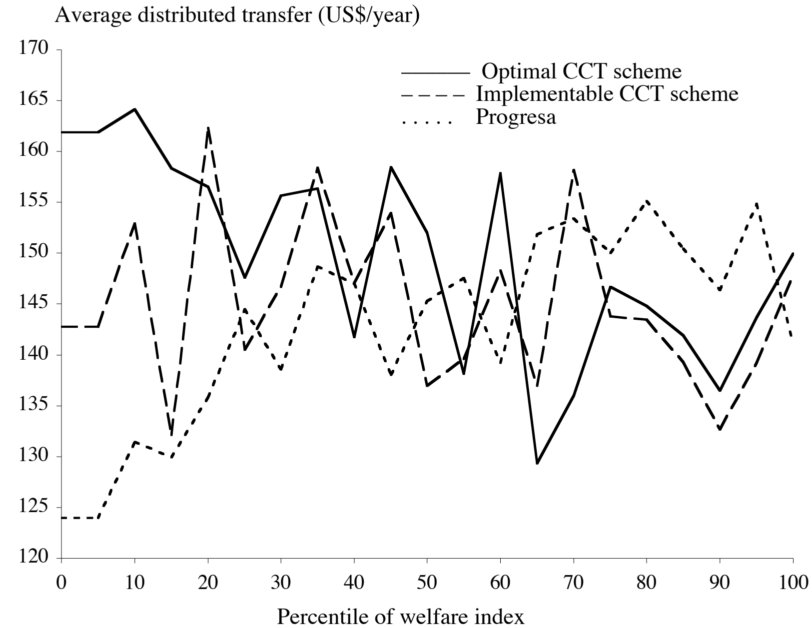


Figure 5. Eligibility and distributed transfers by welfare index

Table 1. Budget for educational grants: Progresa program in the sample villages, 1998

Grade that children could attend	Number of eligible children[1]	Schedule of conditional transfers[2] (US$/year)	Continuation rate (percent)	Budget for enrolled children[3] (US$/year)	(% of total)
Primary 3	1909	70	98.2	114,229	11.8
Primary 4	1811	80	97.8	120,260	12.4
Primary 5	1613	100	97.1	135,626	14.0
Primary 6	1476	135	97.4	166,035	17.2
Secondary 1	1416	200/210	76.7	189,602	19.6
Secondary 2	752	210/235	96.1	134,884	14.0
Secondary 3	551	220/255	96.7	106,028	11.0
Total	9528			966,664	100

[1] Children enrolled in school in 1997 only.

[2] Conditional transfers in secondary school are given separately for boys/girls.

[3] Taking into account the cap on total household conditional transfers. With 10 monthly conditional transfers per school year and an exchange rate in October 1998 of 10 pesos per US$, all transfers can be read as either in pesos/month or in US$/year.

Table 2. Linear probability model of enrollment

	Mean	(1)	Homogeneous impact (2)	(3)	Heterogeneous impact (4)	(5)
Treatment community (dummy)	0.718	0.130**	-0.146	-0.172	-0.091	-0.159
		(0.019)	(0.171)	(0.156)	(0.162)	(0.156)
Conditional transfer*Treatment (US$100/year)	1.215		0.142	0.156+	0.061	0.095
			(0.088)	(0.080)	(0.084)	(0.083)
Conditional transfer*Treatment*Male	0.601				0.003	
					(0.019)	
Conditional transfer*Treatment * (Age –12)	1.239				0.020**	0.016*
					(0.007)	(0.007)
Conditional transfer*Treatment * Father indigenous	0.419				0.037*	0.028
					(0.019)	(0.019)
Conditional transfer*Treatment*No sec. school in village	0.945				0.022	0.037+
					(0.022)	(0.021)
Child and household characteristics						
Conditional transfer (US$100/year)	1.940		-0.015	-0.072	0.006	-0.063
			(0.069)	(0.069)	(0.065)	(0.069)
Male	0.507			0.057	0.073**	0.057
				(0.037)	(0.029)	(0.037)
Age	13.012			-0.090**	-0.130**	-0.110**
				(0.008)	(0.010)	(0.011)
Father is indigenous	0.354			0.027	0.059*	-0.006
				(0.040)	(0.029)	(0.045)
Birth order	2.014			0.016		0.014
				(0.015)		(0.015)
Head is male	0.930			-0.037		-0.033
				(0.044)		(0.044)
Has no father	0.114			-0.015		-0.011
				(0.045)		(0.045)
Father is literate	0.670			0.054+		0.053+
				(0.028)		(0.028)
Father's education	2.491			0.000		0.000
				(0.006)		(0.006)
Has no mother	0.050			0.058		0.057
				(0.075)		(0.074)
Mother is literate	0.621			0.055*		0.057*
				(0.027)		(0.027)
Mother's education	2.351			-0.002		-0.003
				(0.006)		(0.006)
Mother is indigenous	0.372			0.059		0.057
				(0.039)		(0.039)
Mother's age	36.192			0.001		0.001
				(0.001)		(0.001)
Number of children 0-10 years old	2.586			0.002		0.002
				(0.006)		(0.006)
Number of children 11-19 years old	2.781			-0.014		-0.014
				(0.012)		(0.012)
Number of agricultural workers	1.274			-0.031**		-0.030**
				(0.009)		(0.009)
Number of non-agricultural workers	0.314			-0.02		-0.019
				(0.014)		(0.014)
Number of self employed	0.194			-0.039*		-0.037*
				(0.018)		(0.018)

Table 2 (continued)

	Mean	(1)	Homogeneous impact (2)	(3)	Heterogeneous impact (4)	(5)
Number of unpaid family workers	0.332			-0.012		-0.013
				(0.010)		(0.010)
Number of other working adults	0.100			-0.037		-0.035
				(0.028)		(0.028)
Household's maximum education	4.975			0.018**		0.017**
				(0.004)		(0.004)
Total expenditure (US$100/year)	8.055			0.004*		0.004*
				(0.002)		(0.002)
Dwelling has dirt floor	0.696			0.047*		0.043*
				(0.020)		(0.020)
Persons/room in dwelling	5.206			-0.003		-0.002
				(0.004)		(0.004)
Dwelling has water	0.327			0.056**		0.058**
				(0.020)		(0.020)
Rainfed land (ha)	2.059			-3x10^-4		8x10^-5
				(0.002)		(0.002)
Irrigated land (ha)	0.066			-0.009		-0.007
				(0.015)		(0.015)
Herd size	0.878			-0.005		-0.005
				(0.006)		(0.006)
Community characteristics						
No secondary school in community	0.775			0.014	-0.221**	-0.031
				(0.045)	(0.033)	(0.051)
Distance to secondary school (ln of kms)	1.031			-0.130**		-0.129**
				(0.026)		(0.025)
No school in community*Girl	0.384			-0.028		-0.029
				(0.041)		(0.041)
Guerrero	0.174			-0.124**		-0.124**
				(0.044)		(0.044)
Michoacan	0.136			-0.168**		-0.166**
				(0.045)		(0.045)
Puebla	0.159			-0.137**		-0.140**
				(0.043)		(0.043)
Queretaro	0.050			-0.268**		-0.279**
				(0.054)		(0.054)
San Luis Potosi	0.133			-0.163**		-0.161**
				(0.045)		(0.045)
Veracruz	0.281			-0.103*		-0.103*
				(0.041)		(0.041)
Constant		0.636**	0.666**	2.009**	2.428**	2.301**
		(0.015)	(0.134)	(0.204)	(0.186)	(0.231)
Observations		2242	2242	2242	2242	2242
R-squared		0.02	0.02	0.23	0.17	0.23

Standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 3. Heterogeneity: Impact of conditional transfers on the probability of school enrollment by type of child

Treatment variables	Homogenous impact			Heterogenous impact	
	Treatment community Dummy	Conditional transfer Amount	Conditional transfer Amount w/controls	Conditional transfer Amount	Conditional transfer Amount w/controls
Type of child	(1)	(2)	(3)	(4)	(5)
Overall effect	0.130	0.140	0.140		
Boy, 12 years old, non-indigenous, with sec. school in the community (US$200)				0.035	0.031
Boy 14 years old				0.115	0.095
Boy with father indigenous				0.109	0.087
Boy with no secondary school in the community				0.089	0.105
Boy 14 years old, indigenous, with no school in the community				0.243	0.225

Source: Marginal effects based on results from Table 2, with corresponding columns in parentheses.

Table 4. Enrollment rates under alternative CCT schemes

			No program (1)	Universal uniform CCT scheme (2)	Optimal variable CCT scheme (3)	Implementable CCT scheme (4)
	Observations	(%)	Enrollment rates (%)			
All children	2242	100.0	63.2	75.7	81.1	79.4
By probability of enrollment without conditional transfer						
0-40%	354	15.8	27.8	47.2	73.2	57.9
40-60%	583	26.0	50.9	66.1	76.8	71.4
60-70%	376	16.8	64.9	77.8	79.3	81.3
70-80%	392	17.5	74.6	85.8	82.0	87.6
80-100%	537	24.0	90.5	96.1	91.8	94.9
Eligible students						
Without conditional transfer				63.2	55.8	58.2
With conditional transfer				75.7	78.9	79.1
Non-eligible students				–	89.0	80.5
Eligibility (%)				100.0	77.5	77.4
Average transfer value (US$/year)[1]				193.6	236.9	236.3
Cost per additional child enrolled (US$/year)				1151	802	889
Efficiency gain over universal uniform CCT scheme (%)				–	43.6	29.4

[1] Average over the children that take the transfer.

Table 5. Optimal implementable CCT schemes

	Conditional transfer (in US$/year)		
	Base model	With illiteracy	Geographical
	(1)	(2)	(3)
Conditional transfer formula			
Birth order	-12	-11	
Male	-25	-25	
No secondary school in the community	476	502	447
Distance to secondary school (ln(1+kms))	50	49	48
Mother illiterate		26	
Father illiterate		30	
Guerrero	-295	-351	-295
Hidalgo	-278	-327	-283
Michoacan	-246	-288	-253
Puebla	-267	-317	-273
Queretaro	-208	-257	-214
San Luis Potosi	-260	-303	-260
Veracruz	-285	-333	-288
Examples of conditional transfers (US$/year) by children types in State of Guerrero			
School in the community	Not eligible	Not eligible	Not eligible
Oldest, male, with literate parents, and school at 3kms	213	184	218
3rd sibling, male, with literate parents, and school at 3kms	190	162	218
Oldest, male, with illiterate parents, and school at 3kms	213	240	218
Oldest, female, with illiterate parents, and school at 3kms	239	265	218
Oldest, female, with illiterate parents, and school at 6kms	266	292	245
Efficiency gain over universal uniform CCT scheme (%)	29.4	31.0	28.5