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Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks?

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Abstract

Income shocks on poor households are known to induce parents to take their children out of school and send them to work when other risk-coping instruments are insufficient. State dependence in school attendance further implies that these responses to short-run shocks have long-term consequences on children's human capital development. Conditional cash transfer (CCT) programs, where the condition is on school attendance, have been shown to be effective in increasing educational achievements and reducing child work. We ask the question here of whether or not children who benefit from conditional transfers are protected from the impacts of shocks on school enrollment and work. We develop a model of a household's decision regarding child school and work under conditions of a school re-entry cost, conditional transfers, and exposure to shocks. We take model predictions to the data using a panel from Mexico's Progresa experience with randomized treatment. Results show that there is strong state dependence in school enrollment. We find that the conditional transfers helped protect enrollment, but did not refrain parents from increasing child work in response to shocks. These results reveal that CCT programs can provide an additional benefit to recipients in acting as safety nets for the schooling of the poor.

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I. Taking children out of school and sending them to work as risk-coping instruments

Poor people in rural communities are typically exposed to a broad array of shocks. The unemployment or illness of an adult member of the household may imply a loss of income. Illness of any family member can require unexpected health expenditures. Shocks such as droughts, floods, hurricanes, plagues, and earthquakes are likely to affect the incomes of those whose livelihoods depend directly or indirectly on agricultural activities. Responses to shocks to protect family consumption consist in a wide range of creative coping strategies that include drawing down liquid assets held by the household, taking loans, and asking for assistance from members of informal insurance networks. Children can also be used as risk-coping instruments. When households have difficulties in sustaining consumption, children can be taken out of school to save on costs and sent to work to help the household absorb the shock. Children can work on the labor market, in home-based enterprises, or as substitutes for parents in doing household chores. The problem, however, is that children who leave school temporarily may be less likely to subsequently return to school. When there is such state dependence, temporary shocks that induce parents to take their children out of school may have permanent effects on the children's human capital development and future earnings.

Conditional cash transfer (CCT) programs such as Progresa in Mexico, Bolsa Escola in Brazil, and many others around the world (Morley and Coady, 2003) have been used to induce poor parents to send their children to school and care more for their health. These programs have been shown to be effective in raising school achievements (Schultz, 2004). However, this may happen not only because the program brought to school children who would not have gone otherwise, but also because it prevented children exposed to shocks from dropping out. This safety net value of CCT programs, which has yet to be explored, is what we address in this paper.

To investigate the safety net value of conditional transfers, we construct a simple dynamic model of a household's decision regarding child enrollment and work. The model captures five fundamental aspects of this decision: (1) School and work are not incompatible, and consequently do not necessarily compete for time, (2) a child's contemporaneous utility for school enrollment can be positive or negative, (3) there is a school re-entry cost if the child was not enrolled in the previous period, (4) a conditional transfer acts as a price effect on the cost of schooling, and (5) income shocks affect both school and work decisions, and these responses vary across children according to their household income, utility for school, potential wage, and net cost of school.

Model predictions show that a conditional transfer can have a strong mitigating effect on the school enrollment response to an income shock, including by sending to school children with a negative utility for schooling but a high utility for cash as a consequence of the income shock. By contrast, as the conditionality applies to school and not to work, model predictions show that the conditional transfer should not have much of an effect in refraining parents from responding to an income shock by increasing child work.

The model provides estimation equations for the enrollment and work choices that we take to the data using a panel of households from the evaluation component of the Progresa program. The evaluation's randomized design allows us to avoid many of the potential confounds that might otherwise bias our estimates. Results show that there is strong state dependence in schooling and that many shocks are important in pushing children out of school and into work. This is particularly the case for household head unemployment and illness, and for natural disasters that hit the locality. We find that there is a sharp difference in the way conditional transfers mitigate these responses to shocks. A transfer conditional on school assistance largely or fully mitigates the effect of shocks in taking children out of school. By contrast, a conditional transfer does not reduce the rise in child work induced by a negative shock. This shows that the income effect of the conditional transfer is not sufficient to reduce the use of child work as a crucial element of risk-coping strategies.

The remainder of the paper is structured as follows. In section II, we review the results from previous studies on the separate impacts of shocks and of CCT programs on school enrollment and child work. Section III develops a model of a household's school enrollment and child work decision. Section IV presents the Progresa intervention and the data collected in a randomized experiment. Section V provides empirical evidence on the prevalence of shocks and on the sporadic nature of school attendance and work among children in the rural communities observed. Section VI gives the econometric equations that derive from the model for the enrollment and work decisions. Results are presented in section VII for enrollment and work, stressing the role of heterogeneity across children. Section VIII concludes and discusses policy implications for the role of CCT programs as safety nets.

II. Exposure to shocks, dropping out of school, and child labor in recent studies

We analyze in this paper the roles of household income, income shocks, and conditional transfers on a household's decision regarding school enrollment and child work. The literature gives information on each of these effects.

Existence of a positive link between household income and schooling is well established in the literature. Behrman and Knowles (1999) report a review of 42 studies covering 21 countries where they find a positive association between household income and schooling in three fifths of these studies. An important result from these empirical studies, however, is that the marginal effect of an income change on schooling is most often small, suggesting the rationale for school attendance conditionalities in CCT programs.

The link between household income and child work is less well established. According to Basu and Van (1998), child labor is associated with an income constraint on parents, not to their preference for child work (see also López-Calva, 2001). They conceptualize this relation as the "luxury axiom". Higher parents' incomes would allow them to keep their children away from the labor market. Low income parents use child labor while trading off higher current income against lower future child income, as work reduces children's human capital development, and sometimes compromises their future health as well. In an analysis of panel data from Vietnam, Edmonds (2005a) shows a strong decline in child labor as a consequence of improved household per capita expenditure. This relationship has, however, been challenged by other studies. Under the "wealth paradox", children of households with productive assets may work more and study less than the children of less wealthy, and thus poorer, households. This depends, however, on the nature of the assets. Bhalotra and Heady (2003) thus find that children of land rich households are more likely to work than those of land-poor households in rural Pakistan and Ghana. Cockburn (2001) observes that, in rural Ethiopia, some of the household's assets such as small livestock and land owned are child-labor increasing, while other assets such as oxen are child-labor decreasing. In addition, competition between work and school is less rigid than typically argued. Ravallion and Wodon (2000) thus find that increased enrollment in response to a school subsidy in rural Bangladesh occurred without much decline in the incidence of child labor and mainly at the expense of child leisure.

In recent years, another determinant of school attendance and child labor has been analyzed: taking children out of school and using child work as risk-coping instruments when other instruments are insufficient to shelter consumption from income shocks. Using the ICRISAT India panel data for rural households, Jacoby and Skoufias (1997) show how income shocks in a context of financial market failures result in a decline in school attendance. The authors also show that the income shocks that result in lower school attendance are principally covariate as opposed to idiosyncratic.

Several empirical studies have followed the lead of this paper in measuring the impact of uninsured shocks in a context of credit market failures on school enrollment and child labor outcomes. Duryea et al. (2003) show how in Brazil male household head unemployment increases child labor and decreases school advancement, particularly for 16 years old girls. Guarcello et al. (2003) not only observe a similar response for households in Guatemala, but also point out that child labor has a high degree of persistence because children who are sent to work are subsequently less likely to return to school. They show that parent's access to credit and to medical insurance provide risk-coping instruments that help protect children from dropping out of school. Parker and Skoufias (2004) find that, in urban Mexico, idiosyncratic shocks such as parents' unemployment and divorce have no impact on boys' schooling, but reduce school attendance and school attainment among girls. Jensen (2000) and Beegle et al. (2003) show that agricultural shocks increase child labor and reduce school attainment in Côte d'Ivoire and Tanzania, respectively. Access to credit in Tanzania helps protect children from these shocks and keep them at school. Economic crises have also been shown to lead to declines in school enrollment, especially among the poor and younger children. This has been evidenced by Funkhouser (1999) in response to the debt crisis in Costa Rica, Thomas at al. (2003) in response to the financial crisis in Indonesia, and Rucci (2003) in response to the Argentine peso crisis.

Finally, several studies have analyzed the role of cash transfers on a household's schooling and work decision. Income transfers, such as initiation of the South African pension system, have been shown to increase children's schooling and to reduce child labor (Edmonds, 2005b). However, unconditional transfers have small effects on school choices compared to conditional transfers where the condition for the transfer is on school attendance. This role of conditionality in inducing a change in behavior was measured through simulation in estimated school enrollment choices made by children who work in Brazil, allowing to predict the expected impact of Bolsa Escola's conditional transfers (Bourguignon et al., 2003). Analyses of responses to the Progresa program have shown that the conditional transfers have a positive effect on schooling (Schultz, 2004). They also help reduce child work, particularly for boys, while girls respond less as they are better able to combine school and work, expectedly because their work consists more in domestic tasks than that of boys (Skoufias and Parker, 2001). The effect of the conditional transfers is, overall, much stronger on school, to which the condition is attached, than it is on work.

We pose here the question of the joint effect of shocks and conditional transfers on school and work. The literature review suggests that shocks reduce school enrollment and increase child work, while conditional transfers have the reverse effect, increasing school enrollment and reducing child work. The channels through which these effects occur, and their net impacts on outcomes observed, are thus to be determined, questions that we address through modeling and empirical analysis in what follows.

III. A model of the school enrollment and child work decision with shocks and conditional transfers

In this section, we develop a simple dynamic model of a household's school enrollment and child work decision when re-entry into school is costly.[1] A key implication of this model is that a child's current enrollment and work choices depend on the previous period's enrollment status, in addition to current determinants such as preference for school and work, household income, wage opportunity, and net cost

[1] The model we develop was inspired by a model presented in Hyslop (1999) that represents labor market participation decisions when there are search costs.

of school. Within this framework, we then investigate how income shocks affect school and work choices, and the role that conditional transfers can play in mitigating these effects. The model and its predictions help structure the empirical analysis that follows.

3.1. Basic model of the school enrollment and work decisions

Consider a household at time t with a single child and with period utility u function of consumption C_t and of the binary enrollment status S_t and work status W_t of the child. We assume that u is increasing in consumption and decreasing in work, but that children can have either positive or negative utility for school.[2] With a rate of time preference ρ, the discounted value of expected utility at t over an infinite time horizon, U_t, is written:

(1) $$U_t = \sum_{s=0}^{\infty} \frac{1}{(1+\rho)^s} E_t u\left(C_{t+s}, S_{t+s}, W_{t+s}\right).$$

Assuming that there is neither saving nor borrowing, the household maximizes (1) subject to the period t budget constraint:

(2) $$C_t + \left(p - T + c\left(1 - S_{t-1}\right)\right) S_t = Y_t + wW_t,$$

where Y_t is the household's autonomous income, w is wage the child would secure if working, p is a child-specific cost or opportunity cost of schooling, T is a conditional cash transfer given to households of enrolled children, and c is an additional schooling cost associated with re-entry when not enrolled the previous period.

The additional schooling cost for children who had discontinued school stems from various difficulties of re-entering school. The child may, for example, suffer a stigma when he remains behind his cohort of classmates, or the child may have learned to appreciate other ways of life or lost studying habits, or he may have forgotten the materials that are taught in school. The scalar c is intended to capture all these costs.

Also implicit in the formulation of equation (2) is that the child is not time constrained, and can therefore both enroll in school and participate in the labor force. This assumption is reasonable given that the school day is short (usually half-day) and that some children do combine school and work.[3] The assumption also suggests that the opportunity cost of going to school, p, is thus not necessarily equal to the wage.

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[2] The utility function is increasing and concave in consumption. While not essential, we also assume that utility is separable in consumption, schooling, and work, i.e., $u_{cs} = u_{cw} = u_{sw} = 0$.

[3] A more comprehensive model of school and work decisions would allow children to do part-time work, with a flexible number of hours. Such a model is not considered here.

Assuming that Y_t is an iid random variable, the value function is stationary. Given the state variable S_{t-1} and the current and expected future realizations of income Y_t, the value function is:

$$V\left(S_{t-1}\right) = \max_{S_t, W_t}\left[u\left(Y_t + wW_t - qS_t, S_t, W_t\right) + \frac{1}{1+\rho} E_t V\left(S_t\right)\right],$$

where $q = p - T + c\left(1 - S_{t-1}\right)$ is the net cost of schooling (that includes the re-entry cost and the conditional transfer, if applicable) that can be either positive or negative.

For a given work choice, the value q^* that keeps the child indifferent between enrolling and not enrolling in school is the solution to:

(3) $$u\left(Y_t + wW_t - q, 1, W_t\right) - u\left(Y_t + wW_t, 0, W_t\right) = \frac{1}{1+\rho}\left(E_t V\left(0\right) - E_t V\left(1\right)\right).$$

The child enrolls in school if the left-hand side expression is larger than the right-hand side expression, and does not enroll if it is smaller. Because the left-hand side expression is decreasing in q, the child enrolls in school only for $q \le q^*$, where q^* is positive if the child has a positive utility for school and negative if he has a disutility for school.

Similarly, for a given enrollment choice, the child works if the wage offer w is higher than his reservation wage w^* defined by:

(4) $$u\left(Y_t + w - qS_t, S_t, 1\right) - u\left(Y_t - qS_t, S_t, 0\right) = 0.$$

Given Y_t, w, and q, the joint choice of schooling and work, obtained by solving the system of equations (3) and (4), can be summarized as follows:

(5) $$S_t = 1\left[q \le q^*\right] \text{ with } q^* = \begin{cases} q_0^* & \text{if } w \le w_1^* \\ q_0^* + w - w_1^* & \text{if } w_1^* < w \le w_0^*, \\ q^*\left(w\right), \text{ defined by (3), with } W_t = 1 & \text{if } w > w_0^* \end{cases}$$

(6) $$W_t = 1\left[w > w^*\right] \text{ with } w^* = \begin{cases} w^*\left(q\right) \text{ defined by (4) with } S_t = 1 & \text{if } q \le q_0^* \\ w_1^* + q - q_0^* & \text{if } q_0^* < q \le q_1^*. \\ w_0^* & \text{if } q > q_1^* \end{cases}$$

In these expressions, q_0^* and w_0^* are the reservation cost and wage for a child who does not work or go to school, respectively. They are solutions to:

(7) $$u\left(Y_t - q_0^*, 1, 0\right) - u\left(Y_t, 0, 0\right) = \frac{1}{1+\rho}\left(E_t V\left(0\right) - E_t V\left(1\right)\right),$$

(8) $$u\left(Y_t + w_0^*, 0, 1\right) - u\left(Y_t, 0, 0\right) = 0$$

Similarly, q_1^* and w_1^*, which are the reservation cost and wage for a child who works at wage w_0^* or goes to school at a net cost q_0^*, respectively, are solutions to:

(9) $$u\left(Y_t + w_1^* - q_0^*, 1, 1\right) - u\left(Y_t - q_0^*, 1, 0\right) = 0 ,$$

(10) $$u\left(Y_t + w_0^* - q_1^*, 1, 1\right) - u\left(Y_t + w_0^*, 0, 1\right) = \frac{1}{1+\rho}\left(E_t V(0) - E_t V(1)\right).$$

In summary, each child is characterized by a preference for school (that can be positive or negative), present and expected future values of household income Y_t, a wage w, and a net school cost q. Equations (5) and (6) show that a child enrolls in school when his net school cost q is lower than his reservation cost q^*, and works when his wage opportunity w is higher than his reservation wage w^*.

The solution for children with positive utility for school is illustrated in Figure 1 in the space of wage and net school cost (taking household income Y_t and utility for schooling as given). The solid line ABCD represents the positive reservation cost q^* that children are willing to pay for school as function of wage opportunity w, and the dotted line EBCF the reservation wage w^* above which children work as function of net cost q.[4] Children with low net school cost and low wage opportunity will enroll in school and not work. At the opposite corner, children with high net school cost and high wage opportunity will work and not enroll in school. Children with high net school cost and yet low wage opportunity will neither go to school nor work. Finally, children with low net school cost and high wage opportunity will both work and attend school.

The reservation cost and wage are both functions of income, and, except for the small group of children who are indifferent between going to school and working and doing neither (segment BC on Figure 1), the effects of income are unambiguous. Along the segment BC, q^* is increasing and w^* decreasing in income if utility for school is larger than disutility for work, while it is the reverse if utility for school is smaller. To simplify the presentation, we will continue assuming that utility for school is greater than disutility for work. For all other values of wage and cost, q^* is positive and increasing in income if the child has a positive utility for schooling, meaning that the child can bear a higher cost of schooling with higher income. Conversely, q^* is negative and decreasing in income if the child has a negative utility for schooling, suggesting that he has to be paid to come to school when he dislikes it, but

[4] The linearity of the CD and EB segments comes from using a log utility function, but their monotonicity is general.

less so when he comes from a poorer household. Similarly, the reservation wage is an increasing function of income.

3.2. The role of the school re-entry cost and state dependence

The re-entry cost uniformly increases the net enrollment cost q. Its impact is best seen on Figure 1. All children with opportunity cost just below their reservation cost (curve ABCD), such that

$$q^* - c \leq p - T \leq q^*,$$

would remain in school but not re-enroll if they were not in school in the previous period. The re-entry cost induces some children to start working in order to afford the school re-entry cost (along segment EB) and others not to work as they also decide not to re-enter school (along segment BC). With these two opposite effects, the average effect of the lagged enrollment status on work participation is theoretically ambiguous.

3.3. The role of a conditional transfer on enrollment and work choices

A conditional transfer T functions as a price, reducing the net cost of school. For large enough transfers, the net cost, $p - T + c(1 - S_{t-1})$, may even be negative. But consider first the case where the conditional transfer is lower than the school cost. The conditional transfer raises the school enrollment of children regardless of their work choice, by bringing to school children with school cost above the ABCD frontier by less than the transfer:

$$q^* \leq p + c(1 - S_{t-1}) \leq q^* + T. \quad (11)$$

Consider now the case where the conditional transfer T is larger than the opportunity cost of schooling, providing the child a net payment for going to school. In this situation, any child with a positive utility for school will enroll, regardless of his household income or wage opportunity, as $p - T + c(1 - S_{t-1}) < 0 \leq q^*$. This is seen in Figure 1, in the quadrant of negative net school cost. In addition, the positive net payment also induces the enrollment of some children who have a disutility for school, specifically those with low household income and thus high q^*, such that $p - T + c(1 - S_{t-1}) \leq q^* < 0$.

On the work front, the conditional transfer induces an income effect that reduces work of children in school along the segment EB, but induces children along the segment BC to work and makes it possible to go school with help of the transfer. Note that the income effect on w^* is equal to only a fraction of the transfer itself. This can be seen in the expression that defines the reservation wage for these children:

$$u\left(Y_t + w^* - p - c\left(1 - S_{t-1}\right) + T, 1, 1\right) - u\left(Y_t - p - c\left(1 - S_{t-1}\right) + T, 1, 0\right) = 0.$$

While the reservation wage is not a linear function of T for a general utility function, writing its derivative illustrates the point:

$$\text{(12)} \qquad \frac{dw^*}{dT} = \frac{u_c\left(Y_t - p - c\left(1 - S_{t-1}\right) + T, 1, 0\right) - u_c\left(Y_t, 0, 0\right)}{u_c\left(Y_t - p - c\left(1 - S_{t-1}\right) + T, 1, 0\right)},$$

where u_c represents the partial derivative of u with respect to consumption. This derivative is positive, lower than 1, and likely small since it depends on the difference of marginal utilities for incomes that differ by the amount of a school cost. If, as expected, the number of children along the segment BC is smaller than along EB, the effect of the conditional transfer will be an overall decrease in work participation.

3.4. The role of shocks and their long-term effects on school choice

Consider first the case where there is no conditional transfer. As the net cost of schooling is positive, only children with positive utility for school consider going to school. A negative income shock reduces all reservation costs and most reservation wages[5], thus inducing a drop out of school and an increase in work for the children whose net school cost or wage opportunity were close to the reservation values. To see this, let $-dq^*$ and $-dw^*$ denote the declines in reservation values induced by this negative income shock. A child will drop out of school as a consequence of the shock if his net cost of schooling falls in the interval $q^* - dq^* < q \leq q^*$, and will start working if his opportunity wage is in the interval $w^* - dw^* < w \leq w^*$.[6]

As mentioned above, a re-entry cost increases the net school cost if the child was not enrolled the previous year. The consequences of a re-entry cost are particularly acute for a group of children who thus

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[5] As seen above, it increases the reservation wage along the segment BC.

[6] The model assumed no savings and borrowing, making the budget constraint binding on an annual basis. On the credit side, this is not a very distorted view of reality, as there is little credit available for more than a few months to most of the poor. The model also disregards any instruments for consumption smoothing else than taking the child out of school or sending him to work. Note that these actions are, in any case, only used to mitigate large shocks in income that induce a fall in the reservation cost and wage below the child's net cost and wage opportunity. For any smaller shocks, the model predicts no smoothing, leaving, however, space for any other instrument to smooth consumption while the child remains at school. There are cases where even large shocks are sufficiently mitigated by savings or other instruments that taking children out of school or sending them to work is not necessary. Availability of other risk coping instruments thus reduces the role of taking children out of school and sending them to work as a response to shocks. We, therefore, have to interpret the income shock used in the model as being net of the use of other instruments, although all decisions are simultaneously considered.

become casualties of shocks. Consider the case of children with income and preference for schooling such that:

$$q^* - dq^* < p \le q^* < p + c.$$

These children are enrolled in school and would stay in school under normal circumstances of income and a corresponding q^*. However, a negative income shock, such that the reservation cost falls to $q^* - dq^*$, below their opportunity cost *p*, induces them to quit school. In the next period, assuming that income is back to its expected value, their reservation cost is q^*. However, they face the higher cost $p + c$ rather than *p*, and, if this $p + c$ is higher than q^*, they will not come back to school, although they would have come back to school with a cost *p*. A one-time shock thus induces a long-term decline in school achievements.

3.5. The mitigating effects of conditional transfers

In Figure 2, we represent the effect of an income shock on schooling in the space of opportunity cost *p* and reservation cost q^* (which is positive and increasing in Y_t for children with positive utility for school, and negative and decreasing in Y_t for children with disutility for school). Without any transfer, children below the first diagonal, i.e., with $p \le q^*$ are enrolled in school. The effect of an income shock is to induce children with opportunity cost close to q^*, such that $q^* - dq^* < p \le q^*$, to drop out of school. This is represented by the areas marked –A and –B in Figure 2.

The effect of the conditional transfer is to bring to school all the children with opportunity cost *p* between q^* and $q^* + T$. When the income shock hits, it is the children with opportunity cost close to $q^* + T$, such that $q^* + T - dq^* < p \le q^* + T$, that drop out of school (area –C in the figure). The children who are now vulnerable to shocks are, ironically, some of those who would not have enrolled without the conditional transfer (and therefore would not have changed their behavior under an income shock).

Note that children with opportunity cost *p* lower than the transfer *T* will never drop out of school. Dropping out of school would induce a loss of the corresponding net income, which is certainly the last thing a household would want to do in case of an income shortfall.

In addition, when the transfer *T* is larger than the school cost, the CCT program attracts to school children with negative utility for school and low income, such that $p - T \le q^* < 0$. In Figure 2, this is the triangle to the left of the vertical axis. In this case, a negative income shock induces an *increase* dq^* in the reservation cost. This implies that an income shock induces an *increase* in schooling for children with opportunity cost of schooling in the range:

$$q^* < p - T \leq q^* + dq^* - c,$$

where the re-entry cost accounts for the fact that, prior to the shock, they were likely not in school (area marked +D in the figure). The aggregate effect of the income shock on school enrollment is thus a drop in enrollment of children in area –B and a gain in enrollment of children in area +D.

Overall, a conditional transfer modifies the effect of an income shock on the enrollment of three groups of children. It keeps at school children who would be vulnerable to the shock without a transfer (+A+B); it, however, brings to school children who drop out again when facing the income shock (–C); and finally, when school costs are lower than the transfer, it attracts to school children who have a disutility for school but a higher utility for cash as a consequence of the income shock (+D). The net effect on the population of children depends on the distribution of children in the two dimensions of q^* (which captures income, but also utility for schooling) and opportunity cost p, and on the size of the transfer T. However, unless the group of children marginally brought to school by the CCT program (–C) is larger than the number of children in A, B, and D combined, the drop out of school induced by a shock should be lower when a conditional transfer program is in place. Therefore, we expect to observe a strong mitigating effect of a conditional transfer on the negative school enrollment response to an income shock.

Qualitatively, a conditional transfer modifies the effect of an income shock on the work decision in a similar fashion: it keeps from working children who would be sent to work by the income shock, but it does not prevent from returning to work upon an income shock some children who were taken out of the labor force by the conditional transfer (these would show as areas equivalent to A, B, and C in a figure similar to Figure 2, in the space of wage w and reservation wage w^*). Quantitatively, however, these effects should be small for two reasons. First, only the children enrolled in school benefit from the conditional transfer, and second the shift in the wage threshold induced by T is small (as seen by comparing equations (11) and (12)). We, therefore, expect to observe a minimal mitigating effect of a conditional transfer on the work response to an income shock.

IV. Progresa and the data

To analyze the role of shocks and conditional transfers on school and child labor choices, we use the data collected for the evaluation of Progresa, a CCT program in rural Mexico. Progresa was introduced in 1997 offering cash transfers to poor mothers in marginal rural communities, conditional on their children using health facilities on a regular basis and attending school between third grade of primary and third grade of secondary. Children could not miss more than three days of school per month without losing the transfer. The Program was renamed Oportunidades in 2000, and expanded to sixth grade of secondary school and to semi-urban areas. In 2004, it serviced 5 million families at an annual cost of US$2.6 billion (SEDESOL, 2005). The payment schedule is tailored to grade and gender, with primary school children receiving, in 1998, from $70/year in 3rd grade to $135 in 6th grade, and secondary school children receiving from $200/year for boys in first grade and $210 for girls, to $220 for boys in third grade and $255 for girls.

The data consist in a census of households in 506 rural localities, with information in November 1997, and then every 6 months until November 2000. Of these 506 localities, almost two thirds were randomly chosen to be incorporated in the CCT program in May 1998, while the others were kept as control localities until early 2000.[7] We restrict our analysis to the children of eligible households, which are the households classified as poor according to a constructed welfare index measured prior to the program.

We are interested in the school and labor choices of children 8 to 17 years old at any point in time during the period of analysis. Our total sample thus consists in the 52,719 poor children that were 5 to 17 years old in November 1997. Although there are many missing values in the database, the school enrollment status is recorded in each of the seven rounds. Unfortunately, the work status for children at least eight years old was recorded in only six of the rounds (not in the March 1998 round), and information on shocks was irregularly collected, with the complete set including climatic shocks and household employment and health shocks available only in rounds 3 to 6. Our econometric analysis is, therefore, constrained to four rounds of survey from November 1998 to May 2000, all fielded after the beginning of the program.

An issue in the empirical analysis is the extent of sample attrition and missing observations. If attrition is solely related to time invariant child characteristics, this does not cause a problem as all estimations include child fixed effects. But if attrition is induced by shocks and the mitigating effect of Progresa reduces attrition, then this could lead to bias in the coefficient estimates. Since missing information is extensive in this data set, we analyzed in details these samples before undertaking the empirical analysis. Results show that missing information does not appear to be correlated to the

[7] The seven rounds of survey took place in November 1997, March and November 1998, May and November 1999, and May and November 2000. Transfers were in place by the time of the November 1998 round. The control villages had become incorporated into the treatment by the time of the May and November 2000 rounds.

treatment status of the village or to its interaction with shocks, indicating that attrition bias should not be a concern.[8]

V. Empirical evidence on shocks, attendance to school, and child labor

5.1. Prevalence of shocks

Exposure to shocks is high among the rural poor. Table 1 reports the prevalence of different types of shocks at the household and community levels. We consider three types of idiosyncratic shocks at the household level: unemployment of the household head, illness of the household head, and illness of younger siblings. The first two shocks are causes of income loss. The two illness shocks are potential causes for special expenses or need for help at home to take care of the sick. Information on the employment status of the household head is not observed in round 2 (March 1998), and illness shocks are not reported in either round 3 or 7 (November 1998 and 2000). The frequencies reported in Table 1 show a high exposure to risk. Almost one in every four households has experienced unemployment of its head at least once over the six rounds of observation, and about 10% have experienced unemployment more than once. Almost one household in five has experienced illness of its head at least once in 5 rounds of observation. An even more frequent but probably less severe shock is the illness of younger siblings.

Information on climatic shocks was collected in rounds 3 to 6. Each household was asked whether it had experienced certain shocks (drought, earthquake, hurricane, flood, or plague), and whether it had either lost its land, its harvest, or an animal as a consequence of these climatic events. Table 1 reports these individual observations. There is a clear distinction between the very frequent drought shocks which affected 60% of the households at least once over the course of these two years (and more than 25% of the households more than once), and the low frequency shocks (earthquake, hurricane, flood, or plague), although still affecting around 10% of the households over the four rounds. Regrouping the low frequency shocks under the collective name of natural disaster, prevalence is high with 25% of the households reporting having experienced a natural disaster at least once over the four rounds. Since these shocks are really community level events, we construct for each round a measure of intensity of two community-level climatic shocks (drought and natural disaster) using the percentages of households in the community that declare having been affected by one of them. The average intensity of these shocks in

[8] Missing observations on schooling and work are due to children entering the sample after the first observation date because of young age, leaving the sample before the last observation date because they become older than the threshold age used in the survey, and to missing information. Missing observations on school choices for any of these three reasons are positively correlated to some shocks, but are not significantly different across program and comparison groups. Missing observations on work choices are not correlated to shocks.

each round is 24% for drought and 7% for natural disaster. The prevalence of idiosyncratic loss of a harvest follows closely that of drought shocks.

While climatic shocks are clearly exogenous to a specific household, this is not necessarily the case for employment and health shocks, or even to some extent for loss of land, harvest, or animal, since these are partly determined by household behavior. In addition, by imposing regular health checkups as conditionality for transfers, Progresa may decrease the prevalence of illness shocks. As reported in Table 1, we observe a lower health shock frequency in the Progresa than in the non-Progresa villages. For unemployment, there could also be some effect of the Progresa program as it injects large amounts of resources in the communities, although confirming causality would require a more detailed study. On the other hand, drought just happens to have been 10% less frequent in the Progresa villages despite randomization of program placement, but frequency of natural disasters is not different across the two types of villages. In the econometric analysis that follows, we will use child fixed effects to control for problems associated with the potential endogeneity of these shocks.

5.2. Low and irregular school attendance

A serious educational problem in rural Mexico that prompted creation of the Progresa program is low enrollment rates among school age children. Table 2 reports the percent of children not attending school by age category over the two academic years 1998/99 and 1999/2000. Focusing first on control villages, we see that most 8 years old children are enrolled in school in fall semesters. However, 5% of the 11 years old are not attending school at the beginning of each school year. These non-enrollment rates rise dramatically to 14%, 25%, and 36% for the 12, 13, and 14 years old, respectively, with an additional 2–3% in spring semesters. The effect of the Progresa program is seen in the decline, but far from the elimination, of these non-enrollment rates.

A related issue that can be observed with the panel data is high irregularity in school attendance, as children interrupt their schooling for one or more semesters in the course of their education. Table 3 reports on this phenomenon. We qualify as transition into school the observation of a child enrolled in school, while the previous non-missing information was non-enrollment. And, symmetrically, we qualify as transition out of school observations of non-enrollment after observing enrollment. Column 1 reports on all 52,719 children in the database, and columns 2-8 only on those children with complete school information over the seven semesters.[9] This second sub-sample includes children that either became too

[9] Noting school participation by 0 (out), 1(in), or . (information is missing), examples of complete sequences are [1110111] for a child that temporarily dropped out of school in Spring 99 or [0011111] for a child that entered school in Fall 98. Examples of sequences without missing intermediate information are [..10111] for a child with no

old during the survey period (above 16 or 18 depending on the rounds) to be asked about their schooling, or young children that had missing information before entering school for the first time. The striking number is the 8–11% of children that experienced at least two transitions into or out of school. This corresponds to students that either dropped out of school for a period but re-entered afterwards, or reciprocally children that went to school for a period but dropped out again, and all this within a period of only seven semesters. There is no obvious contrast between boys and girls (columns 3 and 4), but there are sharp differences between the younger and older children (columns 5 and 6). Children that were already more than 12 years old in 1997 not only quit school in large numbers (36%) during the period of observation but also experienced large instability, with 19.5% of them moving in or out of school at least twice, and 6.8% at least three times. Comparison of columns 7 and 8 shows that Progresa is effective in reducing both the drop-out rate and irregularity in school enrollment.

These interruptions are likely to have costly consequences on school achievements. Children who lag in age behind their cohort tend to exhibit low performance and have a high probability of abandoning school. Establishing causality between instability and performance would, however, require proper control for selection effects.

5.3. Evidence on child and teenage labor

A similar analysis of children's work patterns indicates that a large number of children did work intermittently during the observation period. Work here is defined as engaging into productive activities -- including wage work, unpaid work outside of home, and work in the family business or farm --, in the week preceding the survey, and is recorded for all children 8 years of age and older in six of the seven rounds (there is no information in round 2). We, however, do not know the number of hours of work and hence cannot distinguish between part-time and full-time work. As seen in Table 4, and considering only children that have not yet graduated from 9th grade, the percentage of children that declare working at least once over the 6 rounds increases with their age, from 11% for those 8-11 years old during the period of observation to 25% for the 11–14 years old, and to 51% for the 13-16 years old. More than half of these working children work intermittently, i.e., have at least 2 transitions into or out of work (e.g., (17+8.3)/39.8 = 63.6% for the 12-15 years old), except for the older group, and 10 to 18% of them experience at least three transitions. This high frequency of intermittent child labor suggests that their work may be used as a mechanism to cope with shocks or temporary needs.

One should not consider work as necessarily incompatible with school, especially in environments where the school day is short. However, only 2 to 3% of the children in fact do both. The

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information in the year 97-98, or [1100…] for a child with no information from Fall 99 on. Finally, an example of sequence with missing intermediate information is [011.111].

most surprising fact, however, is the large percentage of children that neither go to school nor work. At age 12, roughly the time of entry into secondary school, 10% neither work nor study, and this percentage rises to 31% by the age of 15.

VI. The econometric model

The empirical model we use derives from equations (5)-(10). Equation (5) shows that school enrollment S_t depends on the child's last period enrollment status S_{t-1}, all current and expected future realizations of the exogenous variables Y_t, w, p, c, T, and child characteristics influencing u. The variables of interest are the Progresa conditional transfer and the income shocks. In the empirical specification, the transfer variable is replaced by a dummy variable indicating whether the child lives in a village receiving Progresa (which makes him eligible for a transfer), and various shocks are directly accounted for rather than through their effect on income. We use child fixed effects to allow for unobserved time-invariant heterogeneity (including expected future values of exogenous variables) and a time fixed effect to absorb all context variables common to all children. The work decision W_t is a similar equation derived from (6), including the child's last period enrollment status on the right-hand side.

The empirical linear model corresponding to equations (5)-(10) can consequently be written as:

$$(15) \qquad \begin{cases} S_{it} = \gamma^s S_{it-1} + \alpha^s s_{it} + \beta^s s_{it} T_{it} + \delta^s T_{it} + \theta_t^s + \mu_i^s + \varepsilon_{it}^s \\ W_{it} = \gamma^w S_{it-1} + \alpha^w s_{it} + \beta^w s_{it} T_{it} + \delta^w T_{it} + \theta_t^w + \mu_i^w + \varepsilon_{it}^w \end{cases}, \quad i = 1, \ldots, N; t = 3, \ldots, 6,$$

where S_{it} and W_{it} are binary variables representing school and work participation for child i in period t, respectively, γ are the state dependence parameters, s_{it} represent shocks, T_{it} are indicator variables for treatment (Progresa) in the village, δ are average treatment effects, θ_t survey round fixed effects, μ_i child fixed effects that absorb the role of expected income, and ε_{it} time variant heterogeneity terms. The mitigating effect of Progresa on shocks is captured by the interactive term $s_{it}T_{it}$.

Three comments are in order on this specification:

a. The availability of information on shocks restricts the analysis to rounds 3 to 6. As all these observations were recorded after the start of the program, the average treatment effect is absorbed in the child fixed effect. The estimation thus provides the mitigating effect of Progresa on shocks, but not the direct treatment effect.
b. While shocks could be correlated with unobserved child characteristics -- as there likely is a correlation between the household head's average level of unemployment/illness and the schooling of children -- we assume that, conditional on child fixed effects, idiosyncratic shocks are truly

exogenous. As for Progresa, the random assignment in 1997 ensures that it is orthogonal to children's characteristics in 1997.

c. We use a linear probability model for two reasons. First, despite the emerging literature on estimating dynamic binary probit or logit response models (Hyslop, 1999; Chay and Hyslop, 2000), linear probability models are far more tractable and more flexible in the handling of unobserved heterogeneity (Hyslop, 1999).[10] The second, and more substantive, reason is that, with fixed effects probit and logit models, all observations of children that are either continuously in school or continuously out of school drop out of the sample. While this selection would pose no problem to identify the effect of shocks, it does for the impact of Progresa. This is because Progresa itself affects schooling, and thus increases the occurrence of complete schooling sequences and decreases the occurrence of complete out of school sequences. This selection would thus induce a downward bias in the measurement of the Progresa effect.

The dynamic model used for estimating schooling decisions thus becomes:

(16) $$S_{it} = \gamma^s S_{it-1} + \alpha^s s_{it} + \beta^s s_{it} T_i + \theta_t^s + \mu_i^s + \varepsilon_{it}^s,\ i = 1,\ldots,N; t = 3,\ldots,6 .$$

Following Arellano-Bond, equation (16) is estimated by first differencing to eliminate the child fixed effects μ_i:

$$\Delta S_{it} = \gamma^s \Delta S_{it-1} + \alpha^s \Delta s_{it} + \beta^s \Delta s_{it} T_i + \Delta\theta_t^s + \Delta\varepsilon_{it}^s,\ i = 1,\ldots,N; t = 4,\ldots,6 .$$

The parameters of interest in this equation are the instantaneous effects α^s of shocks s_{it} on the enrollment probability and the mitigating effects β^s of the treatment. First differencing creates a correlation between ΔS_{it-1} and the error term $\Delta\varepsilon_{it}^s$. To address this problem, the Arellano-Bond estimator uses the lagged endogenous variables dated up to $t-2$, $S_{i1},\ldots,S_{it-2}$, as instruments for ΔS_{it-1}.

In accordance with the model, the work decision is also a function of the lagged child's enrollment status. However, given that lagged school enrollment is endogenous to the work decision, we choose to omit it from the estimated equations, and simply use as a robustness check the estimation results that include lagged enrollment as an independent variable. As we later verify, its inclusion does not significantly impact on the magnitude of the estimated shock variables. The equation we estimate for the work decision is consequently:

(17) $$W_{it} = \alpha^w s_{it} + \beta^w s_{it} T_i + \theta_t^w + \mu_i^w + \varepsilon_{it}^w,\ \ i = 1,\ldots,N; t = 3,\ldots,6 .$$

[10] There are also a few papers that estimate structural dynamic models of school and work decisions, where unobserved heterogeneity is captured by parameters characterizing a discrete number of types (see Eckstein and Wolpin (1999) and Canals-Cerdá and Ridao-Cano (2004)).

Note that, as there are no pre-treatment observations, the β are identified in both estimations of equations (16) and (17) by simple difference between the effect of shocks in the treatment and control villages. This is sufficient given the random assignment of the program.

VII. Impact of shocks on schooling and child labor, and the mitigating effect of Progresa

7.1. The effects of shocks on school and Progresa's ability to mitigate them

Results reported in Table 5 correspond to an estimated relationship between current enrollment and lagged enrollment, shocks, and mitigation by Progresa for rounds 3 to 6 (equation (16)). We report the impact of individual shocks (columns 1 to 6) and then of all shocks jointly in column 7. Column 8 reports an estimation of the model with child fixed effects and no state dependence (similar to equation (17)).

Considering shocks one at a time, we see that an unemployment or illness shock for the household head reduces the child's probability of enrollment by an average 1.7 percentage points, but that Progresa largely (unemployment) or fully (illness) mitigates these negative effects. Illness of younger siblings has no aggregate effect on the schooling of children in the family. It is notable that drought has no measurable effect on schooling. This result is robust to various econometric specifications and sub-samples of children. A possible explanation for this result is that droughts are sufficiently frequent in Mexico that households have designed ex-ante risk-coping strategies to account for these occurrences.[11] By contrast, natural disasters have a dramatic effect on schooling. A disaster that affects the whole community reduces enrollment by 3.2 percentage points, but this effect is completely mitigated by Progresa. The household's experience of a loss of land, harvest, or animal has a smaller effect (0.4 percentage point) on schooling and it is completely mitigated by Progresa.

When all the shocks are considered together, we loose some precision in the estimation.[12] Column 7 shows that the two main shocks that affect schooling are unemployment of the household head and natural disaster in the locality. While Progresa completely mitigates the natural disaster effect, it only partially protects from the unemployment shock. Column 8 of Table 5 shows that results are similar in a fixed-effect linear probability model without state dependence.

Table 6 analyzes the heterogeneity of effects of shocks on different sub-groups of children. It clearly identifies groups that are more vulnerable than others. In particular, primary school children, indigenous children, and children of agricultural workers are more affected by the unemployment shock

[11] Reardon et al. (1988) find a similar result for the risky Sahelian zone of Burkina Faso.

[12] Correlations are 0.19 between household head unemployment and illness, 0.11 between household head and siblings illness, and 0.16 between drought and natural disaster.

of the household head and by severe natural disasters than secondary school children, non-indigenous children, and children of non-agricultural workers, respectively. Boys are more affected by unemployment of the household head than girls. Conversely girls are more affected by a severe natural disaster than boys. In all cases, Progresa either largely or completely erases the negative effects of shocks on schooling. This is a remarkable result that indicates the safety net value of conditional transfers in periods of negative shocks.

Note that, in control villages, a temporary disaster has both an immediate effect in taking some children out of school, and a long-term impact through the state dependence effect. Even when the shock does not last over the next period, its effect on children that have quit school is that they have an 11% lower probability to be in school the following semester (Table 5, column 7). This is a large effect over the base average enrollment rate of 81.4%. This state dependence effect is highly robust across shocks. In aggregate, a one time natural disaster thus reduces the probability of enrollment by 3.4 percentage points immediately and by 0.37 percentage points the following semester. Table 6 shows that the state dependence is particularly high for secondary school children. Hence, although these children seem less sensitive to shocks, if they do quit school in response to, for example, a household head health shock, their probability of attending school the next semester decreases by 22.8 percentage points over a base value of 66.1%. More generally, any temporary event that takes a secondary child out of school has a large lasting effect. Conversely, on the positive side, any event that induces a secondary child to stay in school, such as receiving a Progresa transfer, has a lasting impact as well. Children in primary school have a lower state dependence than in secondary school, suggesting that their school attendance is more flexible than that of children in secondary school.

Given the frequency of all the different shocks (as seen in Table 1), cumulating their short-term and long-term effects over several years can indeed seriously compromise the schooling of children when they are not protected.

7.2. The effects of shocks on child and teenage labor and Progresa's ability to mitigate them

Estimations of the effects of shocks on child and teenage labor are presented in Table 7. We report results from the fixed-effects model (17) estimated over four rounds of observations, from November 1998 to May 2000. The Progresa effect is here again identified by simple difference between control and treatment villages.

Results show that a household head unemployment shock does not induce children to work more. However, others shocks do. Child labor increases in response to illness of the household head, illness among young siblings, and severe natural disasters in the locality. Progresa does not, however, prevent these child labor responses to shocks.

An interesting result is that drought shocks in the locality reduce children's work in the control villages. The result is robust to various econometric specifications and sub-samples of children. A possible explanation is that local droughts reduce opportunities for children to work, both because farm work is less available and because adult labor supply is also more abundant. In Progresa villages, by contrast, children's work is not affected by drought. This does not mean that children work more in Progresa villages than in control villages, though. The direct effect of Progresa is in fact to reduce child work, as found by Skoufias and Parker (2001). Our own estimate of Progresa's effect on work, using pre-program observations, shows that it reduces child work by 2 to 7% depending on the child's gender and age group. Therefore, children benefiting from Progresa work less, and this is not further affected by drought.

As a robustness check, the last column in Table 7 shows the estimation of the work equation including the lagged school enrollment variable, as derived from the model. While this variable is endogenous as it is correlated with non-observables that likely also affect the current child work decision, its inclusion leaves the coefficients on shocks and Progresa variables largely unaltered.[13]

Table 8 explores heterogeneity in the vulnerability of children to shocks. We observe that the older age group (15-18 years old), which is highly vested in the labor market with a participation rate of 38.8%, is strongly affected by climatic shocks, but not by idiosyncratic household shocks. By contrast, the younger children (8-14 years old), who have a base participation rate of 6.5%, have a lower response to climatic shocks, but increase their work participation by 2 % points in response to parents' health shocks and 1.4 % points in response to siblings' illness. Boys both participate more to the labor market and respond more to shocks than girls. The important steady result, however, is that a Progresa conditional transfer does not mitigate the increased use of child work in response to shocks.

Note that the context of our analysis is one in which some villages were in the Progresa program and others not ex-ante relative to shocks. It is not the case that the Progresa transfer was offered in response to a shock. Shocks therefore inflicted a loss to all households. Because households in the Progresa villages have on average a higher income level (Progresa transfers account on average for 22% of household income), one would expect them to cope better with shocks and not send their children to work as much as the non-program households. This is not the case, though. These results clearly show that the income effect of the Progresa transfer is not sufficient to prevent an increase in child labor in response to negative shocks. What is remarkable, however, is that this increase in child labor is done at no cost in terms of schooling due to the price effect of the conditional transfer.

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[13] We find similar results when we include lagged enrollment in the other work regressions.

VIII. Conclusions and policy implications

Using panel data for villages from the Mexican Progresa program, we observed that shocks are highly prevalent, that many children have irregular periods of school enrollment, and that child labor is very frequent and also sporadic. We developed a model of a household's school enrollment and child work decision that accounts for state dependence in schooling and focuses on the response to shocks and the possible mitigating effect of a conditional transfer. The model predicts a strong mitigating effect of a conditional transfer on the school enrollment response to a shock, but a minimal effect on the child work response.

Econometric results indicate the existence of a strong state dependence effect: children taken out of school are less likely to subsequently re-enroll. Shocks have large effects in taking children out of school. This applies to unemployment of the household head, illness of the household head, and natural disasters in the community. Shocks also induce children to increase their work participation. This shows that, in poor rural communities, children are indeed used as risk-coping instruments in responding to shocks. Because of strong state dependence, short-run consumption smoothing gains for the household obtained by taking children out of school result in long-term losses in these children's human capital.

The Progresa transfers largely or completely protected children from the effect of these shocks on school enrollment. Cash transfers, conditional on schooling, can thus have an important safety net role to play, protecting child education from a range of idiosyncratic and covariate shocks. The Progresa transfers, however, did not prevent child work from increasing in response to shocks. This shows that the income effect of the transfers was not sufficient to affect household behavior with respect to the use of child work in response to shocks.

The Progresa experience indicates that beneficiaries of conditional transfers can be effectively protected from the risk of shocks that would induce them to take their children out of school. This result suggests that CCT programs could be extended to serve as flexible safety nets for vulnerable households that lack access to other risk-coping instruments. They would help these populations prevent short-run shocks from having long-term consequences on the human capital of their children.

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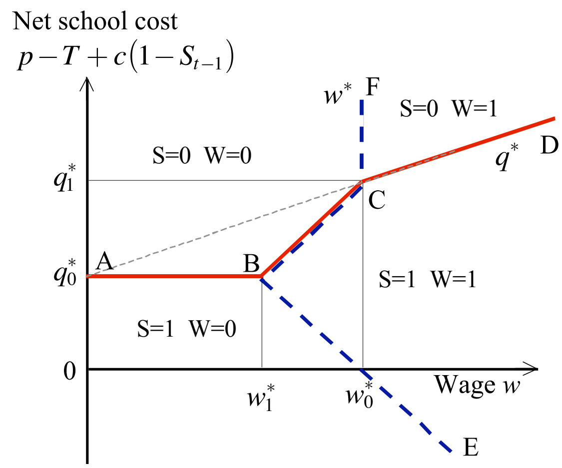

Figure 1. School and work choices as function of school cost and wage
(for given household income and positive utility of schooling)

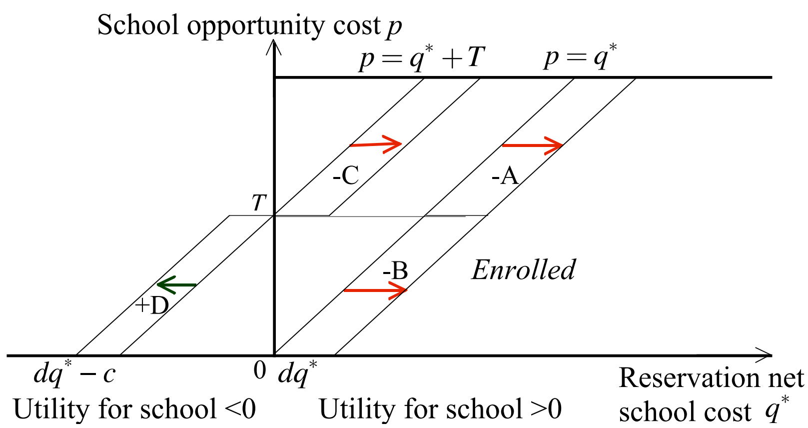

Figure 2. Impact of an income shock on enrollment without and with a CCT program

Table 1. High prevalence of shocks in Mexico's poor rural communities

	Progresa villages	Control villages	Test of difference
Number of households	6,764	4,091	
Percentage of household having experienced a shock:			
Household head unemployed at least once in 6 rounds	22.5	24.2	–
More than once	9.7	11.9	– –
Household head ill at least once in 5 rounds	17.2	20.3	–
More than once	2.9	3.6	–
Children 0-5 years old ill at least once in 5 rounds	42.7	44.5	
More than once	24.3	25.7	
Drought at least once in 4 rounds	59.3	61.9	– –
More than once	25.5	28.6	– –
Harvest lost at least once in 4 rounds	58.6	61.7	– –
More than once	26.9	30.0	– –
Low frequency shock at least once in 4 rounds			
Earthquake	9.3	8.0	+
Hurricane	8.0	9.2	–
Flood	11.5	11.6	
Plague	1.5	1.2	
Natural disaster (earthquake, hurricane, flood, or plague)	25.7	24.7	
Community shocks intensity (percentage of households reporting the shock, average per round)			
Drought	22.6	25.2	– –
Natural disaster (earthquake, hurricane, flood, or plague)	6.9	6.7	

Shocks significantly higher/lower in Progresa villages at 5% (+/–), 1%(++/– –).

Household head employment observed in 6 rounds (not March 98), head of household illness in 5 rounds (Nov-98 to Nov-00), drought, harvest loss, and natural disasters in 4 rounds (Nov-98 to May-00).

Table 2. School non-attendance rate by age, school years 1998-99 and 1999-00

	Children from control villages (%)		Children from Progresa villages (%)	
Age in Fall semester	Average over November 98 & 99	Average over May 99 & 2000	Average over November 98 & 99	Average over May 99 & 2000
8	1.6	4.1	1.3	3.0
9	2.0	3.9	1.4	2.8
10	2.9	5.3	1.6	3.5
11	5.0	7.1	3.3	5.2
12	14.3	17.0	9.2	12.2
13	24.9	27.9	18.4	21.5
14	36.3	37.8	28.9	30.7
15	55.9	56.0	47.0	49.0
Number of observations	19,745	18,500	31,248	29,307

Excluding observations with missing information on enrollment.

Table 3. Discontinuities in school attendance

	All observations (1)	Children with complete schooling data only: All (2)	Boys (3)	Girls (4)	Age in 1997: ≤12 years (5)	>12 years (6)	Poor: Control (7)	Progresa (8)
Number of observations	52,719	16,981	8,798	8,178	13,026	3,955	4,475	7,463
No transition into or out of school	74.4	71.6	71.5	71.7	80.4	42.6	71.6	74.6
Out of school	18.0	6.7	6.8	6.7	0.7	26.8	5.3	5.2
In school	56.4	64.9	64.8	65.0	79.8	15.7	66.3	69.4
One transition	17.2	17.8	18.0	17.6	11.7	38.0	16.8	15.8
Quit school after Nov-97	15.1	16.4	16.9	16.0	10.6	35.8	15.7	14.1
Enter school after Nov-97	2.2	1.4	1.2	1.6	1.2	2.1	1.1	1.8
Two transitions or more	8.3	10.6	10.4	10.7	7.8	19.5	11.6	9.6
Two transitions	6.4	7.6	7.4	7.8	6.0	12.7	8.6	7.0
Three or more transitions	2.0	3.0	3.0	2.9	1.8	6.8	3.0	2.6

Sample constituted of all children ages 5 to 16 in November 1997, observed over 7 semesters from November 1997 to November 2000.

Table 4. Prevalence and sporadicity of work among children not having graduated from 9th grade

Cohorts: Age over 1997–2000	Number of children	Percentage of children by number of rounds in which they work: At least 1	1	2	3	4	5	6	Percent of children with transitions into/out of work: 2	3 or more
8–11	3,291	10.6	9.6	0.8	0.2	0.0	0.0	0.0	6.9	0.6
9–12	3,122	13.9	12.1	1.4	0.3	0.0	0.0	0.0	8.0	0.9
10–13	3,366	18.5	14.8	2.6	0.6	0.1	0.0	0.0	9.9	1.5
11–14	3,024	25.4	18.4	5.0	1.6	0.5	0.3	0.0	11.7	3.1
12–15	2,437	39.8	23.0	10.4	5.2	2.6	1.1	0.3	17.0	8.3
13–16	1,912	51.3	24.3	12.9	9.7	5.8	2.9	0.6	21.5	11.2
14–17	1,574	61.5	21.5	13.5	13.3	11.1	6.8	2.0	25.5	14.9
15–18	1,376	72.7	18.2	13.6	13.9	12.6	11.8	5.3	25.3	12.9

Observations in 6 rounds from Fall 1997 to Fall 2000 (Spring 1998 missing).

Table 5. Impact of state dependency, shocks, and Progresa on school attendance
Linear probability model. Dependent variable: Child at school

	Individual shocks						All shocks	
	AB-FE	AB-FE	AB-FE	AB-FE	AB-FE	AB-FE	AB-FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State dependence								
Child at school last semester	0.115	0.125	0.119	0.127	0.127	0.127	0.111	
	[0.015]**	[0.014]**	[0.014]**	[0.014]**	[0.014]**	[0.014]**	[0.015]**	
Head of household unemployed	-0.017						-0.016	-0.020
	[0.009]*						[0.009]	[0.006]**
* Progresa	0.012						0.010	0.012
	[0.011]						[0.011]	[0.008]
Head of household ill		-0.017					-0.008	-0.005
		[0.008]*					[0.008]	[0.006]
* Progresa		0.019					0.012	0.000
		[0.010]*					[0.010]	[0.008]
Proportion of children age 0-5 ill			-0.004				-0.001	0.001
			[0.005]				[0.006]	[0.005]
* Progresa			0.000				-0.002	-0.006
			[0.007]				[0.007]	[0.006]
Drought severity in locality[1]				0.001			-0.003	-0.002
				[0.007]			[0.007]	[0.005]
* Progresa				-0.004			-0.003	-0.017
				[0.007]			[0.007]	[0.006]**
Natural disaster severity in locality[1]					-0.032		-0.034	-0.049
					[0.009]**		[0.009]**	[0.009]**
* Progresa					0.040		0.040	0.041
					[0.010]**		[0.010]**	[0.010]**
Loss as consequence of natural disaster[2]						-0.004		
						[0.003]		
* Progresa						0.008		
						[0.004]*		
Number of observations	65,716	71,752	68,378	72,264	72,332	72,332	63,121	99,563
Number of children	23,588	24,483	24,041	24,599	24,621	24,621	23,208	31,526
Statistics for 2nd order autocorrelation = 0	-0.18	-0.20	0.44	-0.19	-0.18	-0.18	0.26	
p-value	0.86	0.84	0.66	0.85	0.85	0.85	0.79	

Robust standard errors in bracket; + significant at 10%; * significant at 5%; ** significant at 1%.
Mean value of endogenous variable for sample in (7): 0.814
All models include round and child fixed-effects. Dynamic model estimated with the Arellano-Bond estimator (AB-FE), static model with a fixed-effect specification (FE).
[1] Proportion of households in the locality reporting having experienced a drought or a natural disaster (earthquake, hurricane, flood, or plague) in the last 6 months.
[2] Loss of land, harvest, or animal. Average occurrence of these shocks are 7%, 25%, and 2% respectively.

Table 6. Heterogeneity in vulnerability of schooling to shocks
Dependent variable: Child at school

	Primary school[1]	Secondary school[1]	Boys	Girls	Indigenous	Non-indigenous	Children of agricultural worker	Children of non-ag. worker
State dependence								
Child at school last semester	0.057**	0.228**	0.099**	0.121**	0.088**	0.123**	0.086**	0.114**
Head of household unemployed	-0.028**	0.001	-0.034**	0.002	-0.038**	-0.006	-0.029*	-0.010
* Progresa	0.023+	-0.009	0.020	0.002	0.029+	0.002	0.042**	0.005
Head of household ill	0.010	-0.037*	-0.007	-0.008	0.007	-0.015	-0.018	0.004
* Progresa	-0.006	0.047*	0.021	0.001	-0.008	0.020+	0.020	0.004
Proportion of children age 0-5 years ill	-0.002	0.000	0.000	-0.002	-0.007	0.002	-0.000	-0.003
* Progresa	-0.002	-0.002	-0.003	-0.001	-0.007	-0.000	-0.007	0.008
Drought severity in locality	0.001	-0.010	0.001	-0.006	0.004	-0.006	0.001	-0.008
* Progresa	-0.016*	0.016	-0.001	-0.006	-0.009	0.001	-0.001	-0.011
Natural disaster severity in locality	-0.028**	-0.013	-0.020	-0.050**	-0.049**	-0.013	-0.037**	-0.024+
* Progresa	0.036**	0.021	0.024+	0.057**	0.047**	0.024	0.041**	0.029+
Number of observations	42,198	21,630	32,551	30,552	21,699	41,146	41,286	21,835
Number of children	14,737	8,006	11,938	11,262	7,803	15,302	19,174	13,543
Mean value of endogenous variable	0.926	0.661	0.819	0.808	0.838	0.801	0.825	0.793
Statistics for 2nd order autocorrelation = 0	0.33	0.65	0.14	0.15	-1.76	1.44	-0.04	0.52
p-value	0.74	0.51	0.89	0.88	0.08	0.15	0.97	0.60

Robust standard errors in bracket; + significant at 10%; * significant at 5%; ** significant at 1%.
All regressions include round and child fixed-effects. Linear probability model estimated with the Arellano-Bond estimator.
[1] Primary school includes all children having completed less than 5th grade in Fall 1997; secondary school children have completed 5th grade or more in Fall 97.

Table 7. Impact of shocks on child work and mitigation by Progresa
Dependent variable: Child works

	Individual shocks						All shocks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Head of household unemployed	-0.003						-0.006	-0.011
	[0.009]						[0.009]	[0.009]
* Progresa	-0.016						0.014	0.023
	[0.011]						[0.011]	[0.012]
Head of household ill		0.022					0.022	0.014+
		[0.008]**					[0.008]*	[0.009]
* Progresa		0.013					0.011	0.012
		[0.010]					[0.010]	[0.011]
Proportion of children age 0-5 ill			0.019				0.015	0.018
			[0.006]**				[0.006]*	[0.007]**
* Progresa			-0.001				0.004	-0.008
			[0.008]				[0.008]	[0.009]
Drought severity in locality				-0.074			-0.076	-0.076
				[0.007]**			[0.008]**	[0.008]**
* Progresa				0.017			0.018	0.02
				[0.008]*			[0.008]*	[0.008]*
Natural disaster severity in locality[1]					0.047		0.054	0.049
					[0.012]**		[0.012]**	[0.012]**
* Progresa					0.023		0.016	0.017
					[0.014]		[0.014]	[0.015]
Loss as consequence of natural disaster[2]						-0.019		
						[0.004]**		
* Progresa						0.017		
						[0.005]**		
Child at school last semester								-0.046
								[0.005]**
Number of observations	79,740	82,006	82,006	82,049	82,049	82,049	79,698	66,012
Number of children	23,732	23,906	23,906	23,912	23,912	23,912	23,726	22,037
Mean value of endogenous variable	0.148	0.149	0.149	0.149	0.149	0.149	0.148	0.126
R-squared	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Robust standard errors in bracket; + significant at 10%; * significant at 5%; ** significant at 1%.
Linear probability model. All equations include round and child fixed effects.
[1] Proportion of households in locality reporting having experienced a drought or a natural disaster (earthquake, hurricane, flood,
[2] Loss of land, harvest, or animal. Average occurrence of these shocks are 8%, 27%, and 2% respectively.

Table 8. Heterogeneity in impact of shocks on work and mitigation by Progresa
Dependent variable: Child works

	Age in November 1998				Children of agricultural	Children of non-ag.
	8 - 14	15 - 18	Boys	Girls	worker	worker
Head of household unemployed	-0.013	0.011	-0.021	0.008	0.102	-0.025
	[0.008]	[0.023]	[0.013]	[0.011]	[0.064]	[0.014]
* Progresa	0.025	-0.021	0.023	0.004	-0.060	0.003
	[0.011]*	[0.030]	[0.017]	[0.014]	[0.085]	[0.017]
Head of household ill	0.020	0.027	0.035	0.008	0.031	0.011
	[0.008]**	[0.023]	[0.013]**	[0.010]	[0.012]**	[0.014]
* Progresa	0.001	0.035	0.010	0.011	-0.003	0.010
	[0.010]	[0.029]	[0.016]	[0.013]	[0.016]	[0.019]
Proportion of children age 0-5 ill	0.014	0.018	0.022	0.008	0.015	0.027
	[0.006]*	[0.020]	[0.010]*	[0.008]	[0.008]	[0.015]
* Progresa	-0.001	0.022	-0.004	0.011	0.001	-0.018
	[0.008]	[0.025]	[0.013]	[0.010]	[0.011]	[0.019]
Drought severity in locality[1]	-0.068	-0.104	-0.073	-0.078	-0.059	-0.077
	[0.007]**	[0.022]**	[0.012]**	[0.009]**	[0.010]**	[0.017]**
* Progresa	0.015	0.025	0.018	0.019	0.026	0.025
	[0.008]*	[0.023]	[0.012]	[0.010]	[0.010]*	[0.019]
Natural disaster severity in locality[1]	0.036	0.112	0.067	0.040	0.029	0.113
	[0.011]**	[0.033]**	[0.018]**	[0.014]**	[0.015]	[0.029]**
* Progresa	0.008	0.040	0.020	0.010	0.017	-0.041
	[0.013]	[0.041]	[0.022]	[0.018]	[0.018]	[0.034]
Number of observations	59,255	20,443	41,556	38,121	50,242	29,456
Number of children	17,027	6,699	12,197	11,522	20,544	15,989
Mean value of endogenous variable	0.065	0.388	0.220	0.068	0.131	0.176
R-squared	0.02	0.04	0.03	0.01	0.02	0.02

Robust standard errors in bracket; + significant at 10%; * significant at 5%; ** significant at 1%.
Linear probability model. All equations include round and child fixed effects.
[1] Proportion of households in locality reporting having experienced a drought or a natural disaster (earthquake, hurricane, flood, or plague) in last 6 months.