The length of exposure to antipoverty transfer programmes: what is the relevance for children's human capital formation?

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Abstract

Within social protection, antipoverty transfer programmes have significantly emerged in developing countries since the late 1990s. The effects of long-term participation and the assessment of the response of children's human capital formation to different levels of exposure are still unclear. This paper initially takes into consideration the Baland and Robinson (2000) human capital investment model to look into the economics of the length of exposure to antipoverty transfers. The model is presented in a framework shaped by the participation of households in a human development conditional cash transfer programme (CCT). An empirical contribution is made by estimating a dose-response function following Hirano and Imbens (2004). In this empirical setting, the length of exposure to Colombia's *Familias en Accion* CCT programme is employed as a continuous treatment affecting parental investment in children's human capital. The theoretical and empirical results show that a longer exposure to antipoverty programmes leads to a higher accumulation of years of education and school registration rates.

Keywords

Antipoverty programmes, Social Assistance, Human capital, Conditional Cash Transfers, Dose-response, Generalized Propensity Score, *Familias en Accion*.

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1. Introduction

Recent developments in the evidenced-based implementation of antipoverty transfer programmes have focused on the comparison of treatment and control groups in a binary setting (Ravallion, 2007). Very few research has been done on the assessment of the effects of different levels of length of exposure to these interventions (Behrman et al., 2004; Flores et al., 2011; Kluve et al., 2012). Several attempts have been made to generate evidence supporting the idea that the counterfactual effect of antipoverty programmes on human capital related outcomes varies over time (Gertler, 2004). In the particular case of human development conditional cash transfer programmes (CCT), the results in preventing children to inherit poverty when adults through better human capital may be affected by different levels of exposure. The conceptualisation and empirical evidence in this field is still unclear.

The aim of this paper is twofold. In a first approach, it aims to provide a conceptual theoretical framework based on the children's human capital investment model proposed by Baland and Robinson (2000). This two-period model shows the initial parental decision on children's time allocation between work and school attendance. Poor households unable to save or bequeath force their children to work in order to internalise the negative effects of a lower consumption. A CCT programme is introduced into the model in the form of a continuous length of exposure insofar as children attend school and do not work. The relevance of CCT programmes emerges from the fact that they have been adopted by a significant number of developing countries in the last decade (Barrientos, 2013a, 2013b).

The second approach of the paper provides empirical evidence of the continuous treatment effects of the Colombia's CCT programme, *Familias en Accion*, on children's years of education and school registration. As the identification strategy might be contaminated by potential endogeneity between the outcomes and the length of exposure, a non-experimental model is estimated by following Hirano and Imbens (2004). This analysis explores a rich dataset consisting of the targeting census of the programme that contains more than 1.6 million households with 1.9 million children in the period from 2001 to 2010. The empirical results support the theoretical findings, to the extent that they show that higher exposure to the programme leads to higher accumulation of years of education and higher rates of school registration.

This paper therefore provides an important opportunity to advance the understanding of the effects of the length of exposure to an antipoverty transfer programme on children's human capital. Since CCTs have played an important role in facilitating a higher accumulation of human capital of participating children for over a decade (Rawlings and Rubio, 2005), the main contribution of this paper stands on a theoretical conceptualisation and an empirical approach that has not been explored before. To date, most of the research on the effectiveness of CCTs has been based on conventional impact evaluations in which participants are compared to non-participants. Contrarily, this paper's concern is focused on to which extent the outcomes respond at different levels of exposure of participants to the intervention. Policy implications of these findings are also relevant, in the sense that this analysis can contribute to the implementation of antipoverty transfers accounting for an acceptable levels of exposure.

The organisation of this paper is detailed as follows. The second section develops the Baland and Robinson (2000) model with the intervention of a CCT programme. The third section presents the empirical methodology following Hirano and Imbens (2004) as part of the identification strategy. The fourth section describes the data from the *Familias en Accion* programme. The fifth section presents the results and the dose-response of the years of education and school registration. Finally, the sixth section presents the concluding remarks.

2. The Baland and Robinson model with CCTs

In this section the Baland and Robinson (2000) (BR henceforth) two-period model of household investment in child human capital is adapted with a CCT intervention. The BR model focuses on the parental decision on the allocation of children's time between work and schooling in a context where parents face liquidity constraints and imperfect capital markets. Liquidity constraints imply that households in poverty are severely constrained in their capacity to save or bequeath. The imperfections of the capital markets accessible to poor households prevent them from buffering the reduction in the consumption levels due to the investment in the child human capital. Poverty and imperfect capital markets force altruistic parents to choose inefficiently high levels of child labour. A CCT intervention may modify this choice and lead the households to cope with these constraints considering that the effect of the programme is not constant over time. Adapting the BR model to include the features of CCTs provides an analytic framework to examine the length of exposure of poor households to this type of antipoverty programmes.

The allocation of children’s time in a first period is divided between labour and schooling activities that generate human capital. The model is based on the idea that the consumption level of the household can decrease if the children do not work but study. If parents are not poor, savings and bequests are used to internalise the impact of the investment in human capital of their children on current and future consumption. If child labour is culturally accepted and that there is no enforceable ban on it, poor parents will force their children to work.[1] Specifically, BR explains how poor parents would under invest in the human capital

[1] Ranjan (1999) discusses how poverty in combination with credit constraints and no bequest causes child labour. Similarly, Basu and Van (1998) argue that non-working children from poor households are a luxury good and that once their income rises above a certain subsistence threshold, parents withdraw children from the labour market.

of children in presence of imperfect capital markets and no bequeathing capacity.[2] In other words, non-optimal choices of the model will always lead to high levels of child labour and low levels of human capital accumulation.

The decision is made by parents in two discrete periods, $t = I, II$, over a coexisting life with their children. In the first period, $t = I$, parents have one child whose available time is allocated to child labour in the form of a fraction of this period, $l_c \in [0,1]$. The time that the children do not spend at work, $1 - l_c$, is instantaneously transformed into human capital by the function $h(1 - l_c)$ which is continuously differentiable, strictly increasing and strictly concave.[3] If children work full time in the first period, $l_c = 1$, they will still have one unit of human capital, such that $h(0) = 1$. On the other hand, parents inelastically supply $\bar{L}_p$ constant efficiency units of labour in both periods. Consumption at competitive prices in the first period is equal to the income obtained from the work of parents and children together who earn competitive wages, $w_{p,I}, w_{c,I}$, respectively. If capital markets are imperfect, then parents cannot borrow. Instead, they can transfer part of the household income from the first to the second period in the form of precautionary savings, S, with no rate of return. Savings are essential to allow parents to internalise the impact of child human capital formation on future consumption.

The CCT programme is introduced in the first period not only as a constant term but as a function that depends on the transfer and the fraction of the first period dedicated to the child human capital formation. The decision of parents on school attendance is influenced by the CCT, while the fraction of the children's time allocated to non-market activities is considered as the length of exposure to the intervention. The duration of the participation of the household in the programme will entail some human capital formation activities by the child as required in the co-responsibility. The available time of the children is constrained by the fact that child labour cannot absorb the total time, that is, $l_c \in [0,1)$. This last point is relevant because the parental decision on whether to participate or not in the programme is not addressed as showed in Skoufias (2005). The time devoted to human capital formation is exclusive of child labour, such that both activities cannot be done simultaneously. Besides the restriction on child labour for a fraction of the available time in the first period, the programme's benefits are introduced in the form of an exogenous income embedded in the budget constraint. Given that the participation time determines the total transfer received by the household, the benefits of the programme are defined by the function $cct = f(\$, 1 -$

[2] Savings and bequests are parameters of the utility function of the parents. Bequests are differentiated from inheritance or gifts because they can be allocated according the utility maximization problem according to the parents' will. See Nordblom and Ohlsson (2011) for a further detail on bequests, inheritances and *inter vivos* gifts.

[3] There are no direct schooling costs as they are deemed to be the forgone child labour income. This assumption is realistic, since in some medium income countries school fees or related costs (tuition, uniforms, transportation, books and supplies) are completely subsidised. See for example Jagero (2011).

$l_c|a,h)$, continuous and double differentiable, increasing and strictly concave. This function represents the CCT the household receives after the exogenous transfer, $\$$, combined with the endogenous fraction of the first period devoted to human capital formation activities, $1-l_c$. These elements determine the total transfer given two essential facts: the first one represents the exogenous characteristics of the supply-side or administrative traits of the programme, a. The second, h, represents the exogenous household characteristics that might shape the participation in the programme. Therefore, considering BR setting, the budget constraint in $t = I$ is given by $C_p^I = \bar{L}_p + l_c + cct - S$.[4]

In the second period, $t = II$, parents and children earn wages denoted by $w_{p,II}$ and $w_{c,II}$, respectively. The income of parents is given by the savings from the first period minus the transfers from parents to their children in form of bequests, b. Children earn labour income independently according to the human capital accumulated in the first period. BR highlight the relevance of bequests because if they are positive "...*parents completely internalize the adverse impact of child labor on the future income of their children since, by reducing bequests accordingly, they can compensate themselves for the current income they lose when not making their children work*" (Baland and Robinson, 2000, pp. 664). Thus, the budget constraints for both are given by $C_p^{II} = w_{p,II}\bar{L}_p - b + S$ and $C_c = w_{c,II}h(1-l_c) + b$.[5]

For the sake of simplicity, the BR model assumes one parent and one child. Additionally, firms have a linear technology, wage rates are supposed to be per unit of human capital and equal to one, $w_{p,I} = w_{p,II} = w_{c,I} = w_{cII} = 1$. This simplification implies that there are no fertility choices to be made and that income can be considered in real terms.

BR follow Becker (1991) and formulate a separable utility function for parents, W_p, that depends on the consumption in both periods, C_p^t, and the utility of their children, W_c, weighted by a parameter, $\delta \in [0,1]$, denoting the extent to which parents are altruistic toward their children. Formally:

$$W_p\left(C_p^I, C_p^{II}, W_c(C_c)\right) \equiv U\left(\bar{L}_p + l_c + cct - S\right) + U\left(\bar{L}_p - b + S\right) + \delta W_c\left(h(1-l_c) + b\right) \quad (1)$$

Parents choose the optimal level of child labour, bequests and savings that maximizes their utility function subject to the budget constraints from both periods. The first order conditions are defined as follows:

[4] Parents live along with their children in both periods. This overlap simplifies the analysis but this setting may fail to provide further details of the life of children when they become parents in a third period as shown in Eswaran et al., (1996), which contributes to the analysis of the poverty traps when human capital converges to a steady state.

[5] Bequests are, in fact, transfers from parents to children in the second period that allow them internalize the forgone consumption in the first period with no effects in the consumption in the second period, if credit markets were perfect (parents could borrow scarifying bequests but not future consumption).

$$U'(\bar{L}_p + l_c + cct - S) \cdot f'(\$, 1 - l_c | a, h) = \delta W_c'(h(1 - l_c) + b) \cdot h'(1 - l_c) \quad (2)$$

$$U'(\bar{L}_p - b + S\,) = \delta W_c'(h(1 - l_c) + b) \quad (3)$$

$$U'(\bar{L}_p + l_c + cct - S) = U'(\bar{L}_p - b + S\,) \quad (4)$$

The BR model focuses on the model's efficiency that leads to low choices of child labour. The efficiency of the model emerges when equations 3, 4 and 5 hold, that is, when bequest and savings are positive. If l_c^* is considered as the solution of the socially efficient level of child labour in the first period in absence of the programme, then it can be inferred from these first order conditions that $\partial l_c^*/\partial\delta$ and $\partial l_c^*/\partial\bar{L}_p$ are negative. Therefore, the more altruistic and productive the parents, the lower levels of child labour. Similarly, from these first order conditions the importance of the size of the transfer can be analysed. The existence of the benefits function, cct, has a direct and immediate effect on the household decision in both periods. If l_c^{cct} is the solution to the problem in the presence of the CCTs, one might expect that $\frac{\partial l_c^*}{\partial cct}$ is strictly negative when the cct is equal or higher than the foregone income generated by the child. Otherwise, the result will be the same as that in absence of the programme. Intuitively the restriction of the transfer on the increase of human schooling and its immediate effect is only feasible if $cct \geq l_c^{cct} - l_c^*$. In other words, parents are willing to participate and stay in the programme as long as they are able to cope with the decrease in child labour. This last point has a strong implication for the administrative determination of the value of the transfer over time: if the design of the transfer can predict or observe the forgone income due to a lower engagement of the child in labour activities, then the difference between the human capital levels with and without the intervention can be positive.

When the parent is able to save and bequeath and $cct \geq l_c^{cct} - l_c^*$, the efficient choice of child labour will imply the equality of the marginal human capital achieved by the children and the marginal transfer obtained by the household. From equations 2 and 3 it is known that equation 4 turns into the new following efficiency condition:

$$f'(\$, 1 - l_c^{cct} | a, h) = h'(1 - l_c^{cct}) \quad (5)$$

The efficiency condition of the model shown in equation 5 becomes important when the CCT programme is provided to the household and savings and bequest are positive. At the optimum, the parent will invest in the child's human capital until the marginal variation of the CCT equals the marginal human capital accumulation. Given that in absence of the programme the optimum is denoted by $h'(1 - l_c) = 1$, the interaction of a CCT will imply that the condition $f'(\$, 1 - l_c^{cct} | a, h) \geq 1$ holds. The CCT could lead the household to choose a lower level of child labour even if the parent is able to save and bequeath.

2.1. The second best

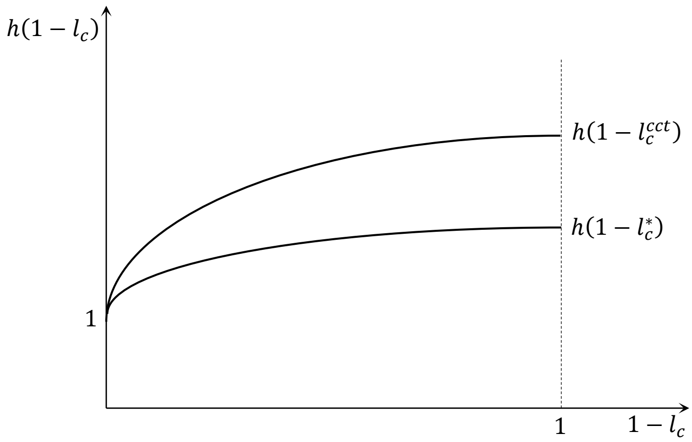
The previous efficient choices are based on the fact that savings and bequests are positive and yield a first best solution. However, poor households to whom CCTs are targeted seldom are able to save or bequeath. In addition, these households face the imperfections of the credit markets which prevent them to transfer income from the second to the first period and, consequently, the child is forced to spend more time on market activities. [6] Therefore, if savings and bequest are zero equations 2 and 3 do not hold and both cannot be introduced into equation 4. Given that any decision on the allocation of the child's time in the first period will be inefficient without savings and bequests, the child labour choice under de presence of the CCT is considered second best solution.

When parents are poor and unable to save or bequeath, equation 5 does not hold in the sense that $f'(\$, 1 - l_c^{cct}|a, h) < h'(1 - l_c^{cct})$. The interaction of the CCT in the problem reveals that inefficient allocation of child labour in the absence of the programme is higher than the inefficient allocation when CCTs are present. Formally, this can be inferred if $h'(1 - l_c^*)$ is the marginal human capital in absence of the programme with l_c^* child labour. Then the condition $h'(1 - l_c^*) > h'(1 - l_c^{cct}) > 1$ represents the second best. This second best condition emerges from the fact that, for zero bequests and savings, $U'(\bar{L}_p - b + S) > \delta W_c'(h(1 - l_c^*) + b) > \delta W_c'(h(1 - l_c^{cct}) + b)$ and that $U'(\bar{L}_p + l_c^* + S) > U'(\bar{L}_p + l_c^{cct} + cct - S) > U'(\bar{L}_p - b + S)$, respectively. In other words, the programme directly decreases the marginal utility of consumption in the first period and the marginal utility of children in the second period due to the increase of the human capital. Hence, even if the household is poor, the programme could be inefficient-improving since the final levels of child labour with interacting CCTs are higher than the efficient outcome but, at the same time, lower than the inefficient level in absence of the programme.

Figure 1 below illustrates the solution to the BR model with and without the intervention of the CCT programme. As the term $1 - l_c^{cct}$ determines the length of exposure to the intervention, it is evident that higher exposure will lead to higher human capital accumulation. This second best solution is consistent with the fact that beneficiary children in CCT programmes are expected to perform better than their parents in the labour markets when adults.

[6] This liquidity constraint and imperfect credit markets is also addressed by Ranjan (1999), who discusses how poverty in combination with credit constraints and no bequest causes child labour. Similarly, Basu and Van, (1998) argue that non-working children from poor households are a luxury good and that once their income rises above a certain subsistence threshold, parents withdraw children from the labour market.

Figure 1. Human capital investment with and without transfers



Source: Author.

One final question emerges from the second best condition regarding whether the CCT helps the parent to cope with either the absence of savings or bequests. In fact, since the function cct interacts in a fraction of the first period, it could help the parents to cope with the absence of savings and with the imperfection of the capital markets. Depending on the size of the transfer function at the optimum, the CCT may be assigned to actual consumption or savings. This last option balances the marginal utility from the consumption in both periods as shown in equation 4. As for bequests, CCTs cannot directly replace them because children do not participate in human capital activities in the second period given that equation 3 does not hold. However, equation 3 could be positively affected by the higher human capital that allows parents to obtain a higher utility from the child's consumption in the second period. CCT programmes allow the parent to internalise the eventual decrease in consumption in the first and second period due to child human investment.

3. Empirical methodology

The empirical methodology of this paper is based on the idea of examining the effects of the length of the exposure of an antipoverty programme on human capital formation of children. This exercise does not test the direct implications of the previous model, but rather throws light on the varying shape of the effect of the programme that the model predicts. The impact evaluations that have detected the effects of antipoverty programmes have focused on the conventional comparison of treated and control groups (Barrientos and Villa, 2013). These evaluations have also assumed the impact of the programme as constant over time with no considerations on its potential variation in response to different levels of exposure. The fact that evaluations consider the effects as constant over time reveals a broad gap in the assessment of these types of interventions. For example, it is not clear whether the increase of 5.1 percentage points in school attendance observed in the initial impact evaluation of *Familias en Accion* will remain constant for different spans of participations

(IFS-Econometría-SEI, 2006). The impact of the intervention can be increasing, constant or even decreasing over time (Behrman and King, 2008). Therefore, this section presents the methodology for the estimation of continuous effects, considering a time-varying effect of the intervention.

There are several underlying challenges that must be taken into account in estimating continuous treatment effects when, as in this case, the length of exposure to an antipoverty programme is regarded as the continuous treatment. The binary comparison between treated and untreated individuals is not suitable as this analysis is not intended to look at the effects on the outcomes in absence of the programme. Instead, it is focused on the continuous effects on the outcomes at different length of exposure for treated individuals. If the length of exposure was assigned randomly one could compare the outcomes of a certain variable by merely differentiating the results from household or individuals at different duration lengths. When randomization is not feasible, the estimation of the continuous treatment effects may be driven by the endogeneity that could arise between the length of exposure and the outcomes. For example, a longer exposure could lead to a higher human capital accumulation and vice-versa. The main challenge of the methodology is, in fact, the mitigation of the potential confoundedness in the estimation of the effects of the programme by considering the treatment as continuous.

Among the feasible methods for the estimation of continuous treatment effects, here it is considered the methodologies introduced by Imbens (2000), Hirano and Imbens (2004) (HI henceforth) and Imbens and Wooldridge (2009) that generalises the conventional binary propensity score treatment effect analysis initially developed by Rosenbaum and Rubin (1983).[7] Despite the availability of some other developments on the generalization of binary treatment effects, the HI has been widely used and internally tested.[8]

The GPS has a number of attractive features. The main assumption of the parametric estimation of the continuous treatments effects proposed by HI is that the assignment of the intervention is random conditional on observational data. Specifically, *"Following Rosenbaum and Rubin (1983) and most of the other literature on propensity score analysis, we make an unconfoundedness or ignorability assumption, that adjusting for differences in a set of covariates removes all biases in comparisons by treatment status."* (Hirano and Imbens, 2004, p. 1). HI demonstrate that a generalization of the binary treatment, which

[7] See for example other methods for continuous treatments developed by Behrman et al. (2004), Florens et al. (2008), Imai and Dyk (2004) and Flores et al. (2011).
[8] Applications of the HI method, including the continuous treatment as length of exposure, are addressed by Bia and Mattei (2008) with loans and grants in the financial sector, Kluve et al. (2012) and Choe et al. (2011) with the effects of the duration of job training programmes on earnings, Heinrich et al. (2012) with the length of exposure, Aguero et al. (2006) with a nutritional benefit of the South Africa's Child Support Grant, and Teixeira (2010) with the effects of the value of the benefits of Brazil's *Bolsa Familia* on labour supply.

they call *Generalized Propensity Score* (GPS), has the same properties of the binary treatment propensity score. The potential confoundedness or endogeneity derived from the dependence of the outcomes on the continuous treatment assignment is controlled by the availability of observed pre-treatment covariates. The subsequent randomness given the control for observational data is commonly known as Conditional Independence Assumption (CIA).

Significant considerations are taken into account regarding HI methodology. The first one is that it relies on the mitigation of the endogeneity between the continuous treatments employing observable pre-treatment covariates. This fact can ignore the existence of unobservable factors that can drive the results under certain circumstances. The second and more importantly, HI suggest a parametric specification of the dose-response function that can force the shape of the estimated effects. As it can be noticed below, the implications of these two considerations are coped by analysing endogeneity in the continuous variable and providing a cubic functional form of the parametric specification.

3.1. Formalization of the HI continuous treatment effects estimation

The framework developed by HI assumes the existence of random sample units denoted by $i = 1, \dots, N$ and a potential outcome, $Y_i(t)$ for $t \in \tau$, which is known as the unit-level dose-response function. In a binary treatment effect framework $\tau = \{0,1\}$, however in the continuous case the treatment variable, τ, is deemed to vary in the interval $[t_0, t_1]$. HI focus their interest on the average continuous treatment effect from the average dose-response function specified by $\mu(t) = E[Y_i(t)]$. The dose-response function would be confounded by a potential endogeneity between Y_i and τ unless the control for observable covariates for each unit i, X_i.

HI simplify the notation by dropping the i and they assume that T is a continuously distributed variable. $Y(T)$ is then a well defined random variable and suitably measurable. The assumption of independence between Y and T is based on the weak unconfoundedness because for each level of treatment the following conditional independence (CIA) holds:

$$Y(t) \perp T \mid X \ \textit{ for all } t \in \tau \tag{5}$$

The CIA leads to the definition of the GPS:

$$r(t, x) = f_{T|X}(t|x) \tag{6}$$

Where $r(t, x)$ is defined as the conditional density of the treatment given the covariates. For the observed units, the GPS is then defined as $R = r(T, X)$.

Similar to the binary propensity score, the continuous treatment preserves the balancing properties of the covariates given the GPS for any level of treatment. That is:

$$X \perp 1\{T = t\} \mid r(t, X) \tag{7}$$

When equation 7 holds, the balancing score property is achieved by the GPS. As HI point out that *"In combination with unconfoundedness this implies that assignment to treatment is unconfounded given the generalized propensity score"* (Hirano and Imbens, 2004, p. 2). In this case, the balancing property is also analysed on the common support region as suggested by Flores et al. (2011). The balancing test is constrained to the common support region, which is obtained by calculating quintiles of the continuous treatment variable, T, and identifying the median of the GPS at each quintile. Borrowing the notation by Flores et al. (2011), the quintiles of T are denoted by $Q_i = \{1, 2, 3, 4, 5\}$ and the value of the GPS at the median of the treatment by $\hat{R}_i^q$, such that for each quintile, *q*, the common support region is given by:

$$CS_q = \left\{i: \hat{R}_i^q \in \left[max\left\{min_{\{j:Q_j=q\}}\hat{R}_j^q, min_{\{j:Q_j\neq q\}}\hat{R}_j^q\right\}, min\left\{max_{\{j:Q_j=q\}}\hat{R}_j^q, max_{\{j:Q_j\neq q\}}\hat{R}_j^q\right\}\right]\right\} \tag{8}$$

3.2. Estimation

The estimation of the average continuous treatment effects implies the estimation and calculation of the GPS and the individual dose-response function. This process consists of four basic stages. The first one is the regression of the observable covariates on the treatment variable, T_i,. The second is obtaining the GPS with the predictions of the previous regression. The third one is the estimation of the individual dose-response function, obtained by regressing the outcome variable on the treatment variable and the GPS. The last one, is the calculation of the average dose-response function for a given treatment level interval.

HI use a flexible parametric approach and define the distribution of the treatment given the covariates as a normal-distributed function:

$$T_i | X_i \sim N(\beta_0 + \beta_1' X_i, \sigma^2) \tag{9}$$

The GPS is then calculated once the parameters β_0, β_1 and σ^2 in equation 4 are estimated. HI suggest a simple normal model as an explicit functional form for equation 6:

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} exp\left(-\frac{1}{2\hat{\sigma}^2}\left(T_i - \hat{\beta}_0 - \hat{\beta}_1' X_i\right)^2\right) \tag{10}$$

The next stage is the estimation of the conditional expectation of the outcome, Y_i, given the treatment variable and the GPS. Since the regression analysis can force the functional form of the treatment effect function, a cubic approximation is specified to facilitate a flexible parameterisation (linear or quadratic approaches are also feasible):

$$E[Y_i|T_i, R_i] = \alpha_0 + \alpha_1 \cdot T_i + \alpha_2 \cdot T_i^2 + \alpha_3 \cdot T_i^3 + \alpha_4 \cdot R_i + \alpha_5 \cdot R_i^2 + \alpha_6 \cdot R_i^3 + \alpha_7 \cdot T_i \cdot R_i \tag{11}$$

Finally, at a given treatment level, the estimates of equation 11 are averaged to obtain the dose-response function:

$$E[\widehat{Y(t)}] = \frac{1}{N}\sum_{i=1}^{N}\big(\hat{\alpha}_0 + \hat{\alpha}_1 \cdot t + \hat{\alpha}_2 \cdot t^2 + \hat{\alpha}_3 \cdot t^3 + \hat{\alpha}_4 \cdot \hat{r}(t, X_i) + \hat{\alpha}_5 \cdot \hat{r}(t, X_i)^2 + \hat{\alpha}_6 \cdot \hat{r}(t, X_i)^3 + \hat{\alpha}_6 \cdot t \cdot \hat{r}(t, X_i)\big) \tag{12}$$

Equation 12 is essential for the inference of the continuous treatment effect. Since the treatment variable is contained in the R_i function, the coefficients that form T_i in equation 11 cannot be interpreted as the average marginal effect of the treatment.

4. Data

The data for the estimation of the effects of the length of exposure to an antipoverty programme are obtained from *Familias en Accion*, a flagship social assistance CCT from Colombia. It was introduced in Colombia in 2001 given the country's negative economic growth in 1999 that triggered a deep economic crisis. The national government responded by adopting the Mexican version of a CCT intervention known as *Progresa/Oportunidades*, which had proven to generate important positive effects on the human capital formation of children. The objective of *Familias en Accion* is dual: it is aimed at alleviating current poverty while preventing children to inherit poverty when adults. The programme delivers a monthly income transfer in cash that averages US$30 conditional on school attendance and health checkups of participating children under 17 years of age. Households in extreme poverty are identified with the application of a proxy means test called *Sisben* (Castaneda, 2005; DNP, 2010). *Sisben* provides a welfare score ranging from 0 to 100, denoting 0 the poorest and 100 the wealthiest household.[9] Exposure to the programme is thus dependent

[9] Once the programme obtains the *Sisben* information of eligible households, its administrators start the advertisement of the registration process. Mothers of eligible households were prioritised as cash recipients, in absence of them, fathers or grandparents were in the second place. The eligible mothers would be invited to the registration windows to sign a document which would compromise them to comply with the co-responsibilities. The registration process could last maximum one week in a selected municipality, after this event no further registration opportunities are given to eligible but unregistered households. Thus, between 60 and 80 percent of eligible households take up the transfers in each municipality.

on the age or school grade of the youngest children in the household, as exit is triggered when children either turn 18 years of age or graduate from school insofar as the household is identified in extreme poverty.[10]

The estimation of equations 9, 10, 11 and 12 relies on the use of the *Sisben* data. The *Sisben* survey is carried out before the programme is introduced in a municipality when potential beneficiaries seldom are aware about the possible eligibility to *Familias en Accion*. The main advantage of using the *Sisben* data is the censual coverage for the lowest groups of income in the country.

The *Sisben* data used in this context is composed by two rounds. The first one consists of the pre-programme classification of each eligible household for the different registration waves. This isolates any potential contamination of the observable covariates required by the estimation of the GPS. Indeed, the pre-programme data were collected during the stage of implementation of the programme between 2001 and 2010. Between 2010 and 2011 the *Sisben* data were rectified by a new survey with a national coverage. The outcomes to be considered for the continuous treatment are generated for the second round of the *Sisben* survey used for the rectification of the socioeconomic conditions of every eligible and ineligible household. Thus, the pre-programme covariates denoted by the X_i vector in equation 8 are obtained from the eligibility *Sisben* survey while the outcomes, Y_i, are obtained by the second round after different spans of participation for every household were completed.

The treatment variable, T_i, is obtained from administrative records. The programme's information system contains the initial registration date of each beneficiary and the current status that allows the calculation of the length of duration (Accion Social, 2010). To avoid additional endogeneity between different lengths of exposure and the selected outcomes, the estimations are focused on current beneficiaries. Differences between the intended and the actual length of duration may contaminate the analysis due to voluntary dropout over the participation period. Hence, the treatment variable is generated from administrative trace of current beneficiaries, ruling out dropouts and retired households.[11]

The initial *Sisben* data contains the pre-program information for 32,247,627 people, corresponding to nearly 72 percent of the Colombian population. After cleaning the dataset

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[10] A non-experimental impact evaluation of the implementation of *Familias en Accion* in the period 2001-2004 conducted by IFS-Econometría-SEI (2006), found that school attendance increased by 5.1 and 7.2 percentage points in urban and rural areas for children between 12-17 years of age, respectively. Similarly, the programme reduced the number of repeated school years by 0.12 for children between 14-17 years. Child labour was almost eradicated by a reduction of 5.5 percentage points in rural areas while the number of weekly worked hours by adults remained unaffected.

[11] Deserter households are those who leave the programme voluntarily while retired those to whom the administrator has stopped the transfers.

and excluding ineligible households, 15,955,265 people were identified as eligible to *Familias en Accion*, representing slightly 3 million households. The pre-programme dataset was merged with the second round containing post-program information by tracking mothers or fathers registered as cash recipients from the programme. Given that the *Sisben* survey between 2009 and 2010 was focused exclusively on low and middle income households, the second round registers 28,489,569 people. After merging pre-programme and post-programme *Sisben* databases the attrition rate rounded 18.2 percent.

Eligible households with a complete set of pre- and post-programme information were finally merged with the administrative data regarding actual participants. Since each participant household has its own registration record and *Sisben* internal identification number, no attrition was found in this step. Finally, a database containing 1,641,551 households and 7,933,935 people was consolidated with complete *Sisben* and administrative information of current participants by June 2011.

4.1. Data description

In this section the variables taking into consideration for the estimation of the continuous treatment effects are detailed. The variables are grouped by their role in the estimation of the equations specified above.

As the HI methodology requires, the first group of variables to be described are those observable characteristics that control for the potential endogeneity between the outcomes and the length of exposure. These variables are obtained from the *Sisben* survey that is carried out prior to the introduction of *Familias en Accion* into each Colombian municipality. Given that the eligibility to the programme considers the household as a whole, no individual variables are included in this part of the analysis. The pre-programme variables are assumed not to be affected by the programme in order to achieve the CIA.

Column 1 of Table A1 in the appendix shows the description of the pre-programme variables. These variables were selected according to the available information which is deemed to determine the length of exposure of beneficiary households to the programme. There are three categories that were taken into account. The first one groups the variables at the household level, which indicate the main assets and demographic characteristics that denote the living conditions of its members. Household information is originated by the pre-programme *Sisben* survey. Most of the variables in this category denote the physical conditions of the households as well as its composition in terms of number of children, presence of members with disabilities and the potential monthly cash transfer from the programme. The second category of pre-programme covariates corresponds to the individual characteristics of the head of the household (recognised as the main bread-winner and decision-maker) and his/her spouse. These individual variables are considered to be important for the programme length of participation as predominately either the head or his/her spouse is the main claimant of the cash transfer directly from the programme. The third category of variables controls for the condition of the economy and political environment that might determine the length of exposure to the programme at the provincial or municipal level (DANE, 2010; Registraduria, 2007). As previously mentioned, the programme was phased in slowly in different regions of the country according to the institutional setting of each municipality. Some of these variables include the size of local population and the political characteristics such as the ruling party at programme's introduction as well as the number of votes. The latter indicate any possible political influence in the adoption of the programme in those municipalities where the local mayor and the national government share the same political affiliation. Finally, since *Familias en Accion* was created in response to an economic crisis, the economic characteristics that take account for the real GDP per capita, local budget and the status of the labour markets are included (DNP, 2011).

4.2. Continuous treatment and outcome variables

Another group of variables required by HI methodology are those outcomes that emerge from the post-programme *Sisben* database (see Table 1 below). The selected outcomes are specified according to the objectives of this analysis and are the intended effects of the design of *Familias en Accion*. Children's year of education and school registration are the two outcomes subject to this analysis.

The continuous treatment variable is presented in relative terms as the elapsed proportion of the maximum length of exposure, which is obtained from the administrative records. It is also consistent with the previous theoretical framework. In this sense, *Familias en Accion* recruits households with children at different ages. The enrolment age or the school grade of the youngest child determines the maximum length of exposure of each household to the programme. All the children enrolled at different ages face a right censorship at the age of 17 or when they graduate from school. The age differentials at enrolment can complicate the comparison of, for example, a child enrolled at 14 years old with an observed and potential exposure of 3 years to another enrolled at 7 years old child with the same length of participation but a potential exposure of 10 years.

The potential complications that emerge from the age differentials are tackled by calculating the elapsed proportion of the maximum length of exposure of the household to the programme. For example, if a child is enrolled in the programme at 13 years old and his household has been participating in the programme for two years, then the proportion of the elapsed proportion of maximum length of exposure is 0.5. This is similar to a child enrolled at 7 years of age and an observed participation length of five years. The proportion of the elapsed proportion of maximum length of exposure allows the comparability of children at different ages of enrolment by avoiding right censorship and reference to specific time units. Hence, for each household *i* the continuous treatment variable (parameter T_i) is defined as:

$$T_i = \frac{elapsed\ years\ of\ participation_i}{18 - age\ of\ youngest\ child\ in\ the\ household_i} \quad (13)$$

Table 1 below shows the average continuous treatment variable. As it can be noticed, overall, households average a proportion of 0.36 of maximum participation, which indicates that on average they still have most of the intended participation length to be completed.

Table 1. Averages of continuous treatment and outcome variables (standard errors in brackets)

Treatment and outcome Variables	Overall
Continuous treatment variable:	
Elapsed proportion of maximum length of exposure	0.368
	[0.188]
Current children:	
Children's years of education (enrolled at 7yo) *	4.169
	[2.148]
Children's school registration (enrolled at 7yo - proportion) *	0.921
	[0.270]
Number of observations (households)	1,641,551
Number of observations (children 7 - 17yo)	1,976,913

Source: DNP (2011); Accion Social (2010); DANE (2010); DNP (2010); Registraduria (2007).
Notes: (1) * Refers to children that were enrolled in the programme at seven years old. (2) Standard errors in brackets.

Now the variable description focuses on the outcome variables. These variables refer to the human capital formation of children, which is the main spotlight of the programme on its objective of breaking the intergenerational transmission of poverty. This analysis takes into consideration the case of those children that were enrolled in the programme at 7 years of age. Children enrolled at 7 years of age allow the assessment of the whole schooling trajectory of each child under the influence of *Familias en Accion*. Indeed, children starting the programme at 7 years offer an opportunity to obtain the continuous treatment effects by ruling out those children with short length of exposure due to a late enrolment. Children enrolled in the programme at 7 years old have an average of 4.17 years of education and a proportion of 0.92 in school registration. The evolution of these outcomes is presented along with the resulting dose-response analysis.

5. Results

This section shows the results of the estimation of the dose-response and treatment effect functions as specified by equations 9, 10, 11 and 12. The results are detailed in the three stages that involve the calculation of the GPS, a balancing test of conditional independence and the calculation of the dose-response functions for each selected outcome.

5.1. GPS estimation

As specified by equation 9, the calculation of the GPS requires the estimation of the conditional expectation of the continuous treatment given the pre-programme covariates. This is achieved by running a linear regression of the household characteristics on the elapsed proportion of maximum length of exposure.

Most of the covariates or household characteristics were significant in the analysis. Column 2 in Table A1 in the appendix presents the result of the estimation of the treatment variable given the pre-programme variables. The results are revealing according to the bias reduction of the elapsed proportion of maximum length of exposure. The significant variables show that poorest obtain lower exposure to the cash transfers. On the other hand, the macro-level variables reveal that political variables do not discriminate between longer or shorter exposures.

The calculation of the GPS entails the prediction of the residuals of the linear regression of the elapsed proportion of maximum length of exposure on the covariates. In fact, equation 10 shows the arithmetic transformation of the residuals into a new variable containing the GPS. The GPS is then introduced as a control variable in the estimation of the dose-response function.

5.2. Balancing test

One of the assumptions made by the estimation of the continuous treatment effects is the conditional independence between the outcomes and the treatment variable given the GPS. After the estimation of the elapsed proportion of maximum length of exposure given the covariates, it is feasible to compare the relation between the continuous treatment and the covariates controlling for the GPS. Regression analysis with bootstrapped standard errors is used to make this comparison, following the suggestions by Imai and Dyk (2004).

Columns 3 and 4 in Table A1 in the appendix show the results of the balancing test. Each cell corresponds to a linear regression of the continuous treatment variable and the continuous treatment controlling for the GPS on each covariate on the common support region. The coefficients in the first column (continuous treatment) would be significant if the covariate is endogenous to the continuous treatment. The second and third columns of coefficients (continuous treatment with GPS) would be non-significant if the GPS complies with equation 7.

The most striking result to emerge from this balancing test is that the GPS is able to reduce the bias generated by the endogeneity between the continuous treatment and the pre-programme covariates, especially on the common support. On one hand, as shown in the referred table, most of the coefficients associated to the covariates were significant at some significant level below 10 percent. On the other, the column of coefficients controlling for the GPS apparently manifest a bias reduction. In fact, when the GPS is introduced into the regression analysis the low significant levels vanish for most of the covariates. This balancing test on the common support demonstrates the potential capacity of the GPS for complying with equation 5, which states that the outcomes are orthogonal to the treatment given the GPS. Given the robust bias reduction offered on the common support, the dose-response functions are estimated on this region.

5.3. Dose-response: effects of the exposure to *Familias en Accion*.

The order of the presentation of the estimation results of the dose-response functions is led by the previous description of the selected outcomes. The main focus is based on the primary objectives of the programme that entail the human capital of children during their schooling age (years of education and school registration).

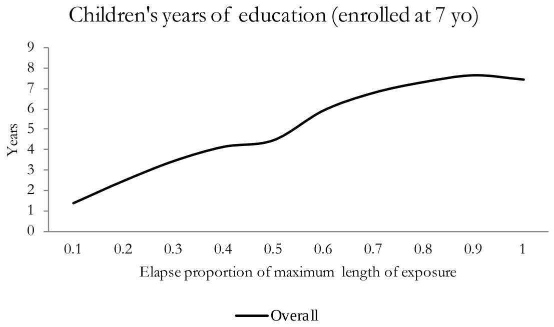
Table A2 in the appendix provides the results on the estimation of equation 11. With a cubic specification, the continuous effects on years of education were estimated by linear regression, while the effects on school registration were estimated by binomial Probit regression. As it can be seen, the continuous treatment variable obtained significant coefficients. The estimated coefficients are used to predict the dose-response function shown in equation 12. Following Bia and Mattei (2008), the focus of analysis is the graphical display of the predicted estimates for the dose-response function along with the bootstrapped confidence intervals at 95% with 200 replications.

As robustness check, the dose-response function is estimated with another specification. This is done by considering a quadratic parametric shape of the regression functional form. If the significance of the coefficients is different from the estimated cubic form, then the results could be compromised by the specification of the dose-response function. The second part of table A2 shows the estimations of the quadratic specification of the dose-response function. These results suggest that the significance and sign of the estimated coefficients are not sensitive to the specification of the functional form, which corroborates the robustness of the suggested dose-response function.

Figure 2 shows the average years of education of children enrolled at seven years of age, which follow an increasing trend until the length of exposure reaches 0.9. On the other hand, Figure 3 shows the same outcome variable adjusted by the GPS, which indicates that the number of years of education responds positively to the elapsed proportion of maximum length of exposure. The dose-response function reveals that children participating in

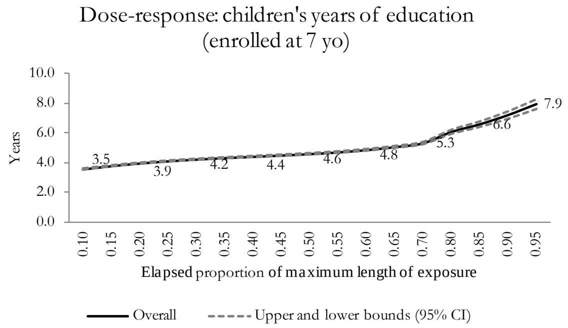
Familias en Accion can obtain between 3.5 and 7.9 years of education. There is a considerable difference of 4.4 years of education between the least and the most exposed to the programme. There is a faster response after the exposure reaches 0.8.

Figure 2. Years of education.



Source: DNP (2011). Calculations: Author.

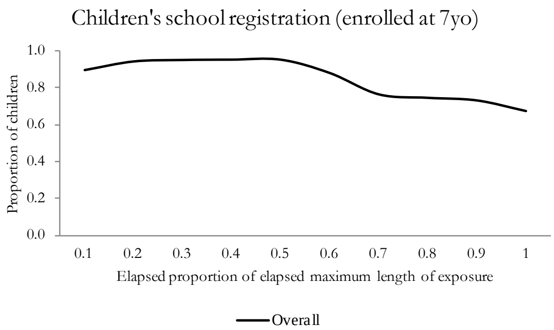
Figure 3. Years of education adjusted by GPS.



Source: DNP (2011). Calculations: Author.
Note: linear regression predictions.

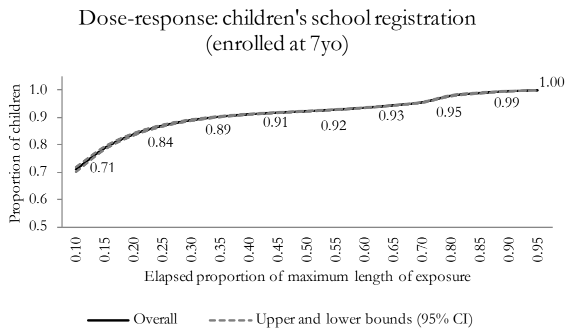
The results of the probability of being registered at school for children that were enrolled at 7 years old are presented in Figure 5. Despite Figure 4 shows that school registration declines, when it is adjusted by the GPS the difference in the probability given an exposure of 0.1 and 1 is 29 percentage points. When children's are exposed to the programme from the initial school enrolment they achieve the maximum probability of school registration once they are fully exposed. The slope of the dose-response function is notably increasing, reporting a difference in the probability of being registered at school of 20 percentage points between an elapsed proportion of exposure from 0.1 to 0.45. This result is consistent with the outcome of years of education, which manifest a positive response as the exposure increases.

Figure 4. School registration.



Source: DNP (2011). Calculations: Author.

Figure 5. School registration adjusted by GPS.



Source: DNP (2011). Calculations: Author.
Note: Probability estimates.

In sum, these estimations have shown that *Familias en Accion*, an antipoverty programme in the form of CCTs, generates positive continuous effects on children's human capital. The longer the exposure to the programme, the higher the years of education and school registration rates that result. This result is consistent with a previous theoretical approach, which predicts a higher investment in human capital of households in poverty with limited saving capacity.

6. Conclusions

This paper has examined the implications of the length of exposure of participants in antipoverty programmes by looking into a theoretical setting of the implementation of a CCT and exploring the empirical evidence obtained from *Familias en Accion*. Contrary to previous impact evaluations based on the single comparison of participants and non-participants, this approach allowed the analysis of the response of the outcomes to different levels of exposure in a non-experimental framework. By modifying the Baland and Robinson (2000) children's human capital model, the understanding of the role of the CCT at higher levels of exposure can predict higher levels of human capital accumulation. Whilst the empirical evidence did test the direct outcomes of this theoretical model, it did throw light on the time-varying shape of the programme's effect.

The evidence from this study suggests that the full exposure of children in poverty to the programme can contribute to their human capital formation, to the extent that a higher exposure translates into higher years of education and higher rates of school registration. In this sense, it has been proven that long-lasting programme participation does not generate trivial or negative effects on children's expected welfare condition when they become adults. Instead, the assumption that children equipped with higher human capital can experience upward welfare mobility in the future is supported by the fact that longer exposure to CCTs can accelerate this process in the context of extreme poverty and deprivation.

A policy implication of these findings is that the implementation of antipoverty programmes aimed at increasing children's human capital should consider a full length of exposure until participants complete the whole school cycle. In particular, antipoverty programmes that intend to deliver transfers to households with children in extreme poverty for a limited time window can rely on this evidence to allow participation until the highest levels of years of education and school registration rates are achieved.

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Appendix

Table A1. Averages of pre-programme variables and estimates.

Pre-programme covariates (proportion)	(1) Means and SD	(2) Estimates	(3) Balancing test	(4)
Household level				
Electricity	0.856	0.002	-0.059	-0.012
	[0.351]	(0.001)	(0.017)	(0.029)
Sewer	0.366	-0.000	-0.003***	-0.089
	[0.482]	(0.001)	(0.000)	(0.054)
Garbage collection	0.456	-0.000	-0.00***	-0.001
	[0.498]	(0.001)	(0.000)	(0.036)
Running water	0.615	-0.001**	-0.099***	-0.056
	[0.487]	(0.000)	(0.026)	(0.099)
Without toilet	0.284	-0.006***	0.095***	0.049
	[0.451]	(0.001)	(0.024)	(0.068)
Type of dwelling:				
House or apartment (flat)	0.898	0.006***	0.045***	0.060
	[0.302]	(0.001)	(0.008)	(0.072)
Wall construction material:				
Bricks	0.508	0.010*	-0.005	0.006
	[0.500]	(0.006)	(0.013)	(0.003)
Floor construction material:				
Concrete	0.513	-0.003***	-0.086***	-0.027
	[0.500]	(0.000)	(0.019)	(0.044)
Number of rooms [a]	2.517	-0.000	0.117***	-0.062
	[1.311]	(0.000)	(0.030)	(0.110)
Number of bedrooms [a]	1.773	-0.000	0.101***	-0.060
	[0.845]	(0.000)	(0.020)	(0.066)
Households in the dwelling	1.149	-0.011***	-0.032***	-0.014
	[0.531]	(0.000)	(0.008)	(0.014)
Household members [a]	6.421	-0.003***	-0.149***	-0.127
	[2.852]	(0.000)	(0.068)	(0.241)
Mean household age [a]	21.962	-0.000	4.613***	4.350
	[8.107]	(0.000)	(0.192)	(3.048)
Household with pregnant woman	0.082	-0.037***	-0.115***	-0.124
	[0.274]	(0.001)	(0.003)	(0.092)
Household with disabled member	0.083	0.007***	0.034***	0.012
	[0.276]	(0.001)	(0.003)	(0.019)
Average age of children [a]	7.491	0.004***	0.001***	0.000

Pre-programme covariates (proportion)	(1) Means and SD	(2) Estimates	(3) Balancing test	(4)
	[3.755]	(0.000)	(0.000)	(0.000)
Age of the youngest child [a]	4.564	0.000***	0.002***	0.000
	[6.308]	(0.000)	(0.000)	(0.000)
Household with children under 6yo	0.701	-0.11***	-0.502***	-0.021
	[0.458]	(0.001)	(0.011)	(0.026)
Household's children attend school	0.726	0.087***	0.396***	0.260
	[0.446]	(0.000)	(0.013)	(0.300)
Ownership of the dwelling	0.513	0.007***	0.147***	0.048
	[0.500]	(0.001)	(0.013)	(0.051)
Assets:				
Fridge	0.280	-0.000	-0.053***	-0.218
	[0.449]	(0.000)	(0.022)	(0.023)
TV	0.664	0.000**	-0.060***	-0.023
	[0.463]	(0.000)	(0.023)	(0.036)
Cooking fuel:				
Firewood, charcoal.	0.474	0.012***	0.226***	0.173
	[0.499]	(0.003)	(0.034)	(0.114)
Type of illumination:				
Electricity	0.855	0.001	-0.061***	-0.013*
	[0.353]	(0.001)	(0.018)	(0.011)
Maximum monthly cash transfer (US$) [a]	27.16	0.000***	9.933***	7.456
	[21.536]	(0.000)	(0.227)	(5.978)
Head of the household				
Male	0.722	-0.004***	0.043***	0.022
	[0.448]	(0.001)	(0.009)	(0.345)
Age [a]	42.82	0.000***	6.836***	-0.313
	[14.857]	(0.000)	(0.245)	(0.790)
Years of education [a]	3.613	-0.000***	-0.953***	-0.671
	[3.054]	(0.000)	(0.119)	(0.988)
Married or cohabitant	0.745	-0.001*	0.035***	0.081
	[0.436]	(0.001)	(0.007)	(0.075)
Employed	0.732	0.005***	0.028***	0.065
	[0.443]	(0.000)	(0.006)	(0.083)
Employed with health benefits	0.030	-0.007***	-0.010***	-0.517
	[0.170]	(0.001)	(0.003)	(0.679)
Spouse's age [a]	28.44	0.000***	6.439***	3.685
	[20.094]	(0.000)	(0.269)	(4.684)
Spouse's years of education [a]	2.922	0.000	-0.557***	0.138
	[3.127]	(0.000)	(0.093)	(0.144)

Pre-programme covariates (proportion)	(1) Means and SD	(2) Estimates	(3) Balancing test	(4)
Employed spouse	0.089	0.002***	-0.022***	-0.009
	[0.284]	(0.001)	(0.009)	(0.010)
Macro-level variables				
Local population [a]	236,948	-0.000*	-344,423***	-399,650*
	[512,059]	(0.000)	(116,017)	(247,653)
Ruling party of the mayor at enrolment				
Officialist or coalition party	0.2666	0.048	0.003	-0.002
	[0.442]	(0.038)	(0.054)	(0.054)
Opposition party	0.2328	0.026	0.044	0.039
	[0.423]	(0.037)	(0.028)	(0.030)
Votes obtained by ruling party	0.402	0.000	1.116	0.643
	[0.193]	(0.001)	(1.021)	(0.943)
Real provincial GDP per capita (US$) [a]	3,599	-0.000***	-188.8**	-132.5
	[1,744]	(0.000)	(87.76)	(144.9)
Share of agriculture in provincial GDP	0.126	0.000	2.560***	2.334
	[0.057]	(0.000)	(0.705)	(2.145)
Local public per capita budget (US$) [a]	63.90	0.000	-22.68***	-11.54
	[60.04]	(0.000)	(8.190)	(8.654)
Provincial employment rate	0.519	0.000**	1.634***	1.544
	[0.040]	(0.000)	(0.435)	(2.154)
Provincial unemployment rate	0.120	0.001***	0.105	0.139
	[0.027]	(0.000)	(0.175)	(0.449)
Number of observations (households - all columns)				1,976,913
R-square (2 column)				0.237

Source: DNP (2011); DNP (2010); Accion Social (2010); DANE (2010); Registraduria (2007).
Notes: (1) Column 1 corresponds to descriptive statistics (standard deviations in brackets); column 2 shows the coefficients for the GPS estimation (robust standard errors at the municipality-level in parenthesis); columns 3 and 4 present the balancing test: column 3 shows the coefficients of the regression of the continuous treatment variable on each outcome; column 4 accounts for the GPS in the common support region (robust standard errors at the municipality-level in parenthesis). (2) a This variables are not in proportional terms. (3) US$ values are calculated with nominal exchange rates. (3) * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table A2. Dose-response estimation

Dependent variable / Outcome	Treatment	Treatment^2	Treatment^3	GPS	GPS^2	GPS^3	Treatment*GPS	R-square
A. Current children (Cubic):								
Children's years of education (enrolled at 7yo)	7.764***	-23.15***	21.89***	-1.819***	1.296***	-0.298	0.992***	0.51
	(0.707)	(2.221)	(2.072)	(0.553)	(0.393)	(0.089)	(0.131)	
Children's school registration (enrolled at 7yo)*	11.36***	-21.81	15.54***	0.076	0.013	0.003	-0.056	0.18
	(0.616)	(1.759)	(1.520)	(0.120)	(0.035)	(0.092)	(0.106)	
B. Current children (quadratic):								
Children's years of education (enrolled at 7yo)	3.202***	-0.686**		-0.191*	0.115***		0.110***	0.47
	(0.329)	(0.324)		(0.111)	(0.032)		(0.007)	
Children's school registration (enrolled at 7yo)*	6.114***	-3.793		0.129	0.061*		-0.564***	0.18
	(0.365)	(4.759)		(0.127)	(0.036)		(0.094)	

Source: DNP (2011); Accion Social (2010); DANE (2010); DNP (2010); Registraduria (2007).
Notes: (1) Coefficients are estimated by linear regression and binomial Probit (indicated by *) controlling for age, gender and urban-rural location. (2) Estimations on the common support. (3) Bootstrapped standard errors with 300 repetitions. (4) * Significant at 10%; ** Significant at 5%; *** Significant at 1%.