Assessing the Impacts of School Subsidies in Bolivia

Werner Hernani-Limarino
Fundacion ARU

June 15, 2011

Outline

1. The *Bono Juancito Pinto* Subsidy
2. Simple Model of School Attendance
3. Estimation Methods
4. Results
5. Conclusion

Bolivia's school subsidy program, *Bono Juancito Pinto*

- **Objectives**
  "to break the intergenerational poverty traps by providing incentives for regular school attendance".
- **Treatment**
  a relatively small cash transfer (less than 30 dollars) given annually to children conditional on:
  - being enrolled into a public school, and
  - having a *regular* school attendance - at least 80% of the regular days.
- **Coverage**
  - Grades 1 to 5 since 2006,
  - Grade 6 since 2007
  - Grade 7 to 8 since 2008
- **Costs**
  around 36 to 54 million of US dollars.

Notation

Let

- c be the household consumption,
- y its household income net of the child's earnings,
- w its children wage, and
- s an indicator of whether the child attends school or not

No policy scenario

The household utility maximization problem:

$$\max_{s} U(c, s, \mu) \tag{1}$$
$$\text{s.t.: } c = y + w(1 - s)$$

CCT scenario

The *new* household utility maximization problem:

$$\max_s U(c, s, \mu) \tag{2}$$

$$\text{s.t.: } c = y + w(1 - s) + \tau s \tag{3}$$

$$= (y + \tau) + (w - \tau)(1 - s)$$

$$= \tilde{y} + \tilde{w}(1 - s)$$

$$\tag{4}$$

Optimal Choices

1. No policy scenario

$$s^* = \phi(y, w, \mu) \tag{5}$$

2. CCT scenario

$$s^{**} = \phi(\tilde{y}, \tilde{w}, \mu) = \phi(y + \tau, w - \tau, \mu) \tag{6}$$

Asses the Impact of CCCT policy

1. With pre-program data -data collected before the implementation of the policy
   the effect of the policy can the estimated with the counterfactual

$$\phi(y+\tau, w-\tau, \mu) - \phi(y, w, \mu) \tag{7}$$

2. With post-program data -data collected after the implementation of the policy,
   the effect of the policy can the estimated with the counterfactual

$$\phi(y, w, \mu) - \phi(y-\tau, w+\tau, \mu) \tag{8}$$

Independence Assumption

Assume that **conditional** on a vector of family characteristics, x, unobserved heterogeneity distribution is independent of both, household income and wages.

$$f(\mu|y, w, x) = f(\mu|\tilde{y}, \tilde{w}, x) \tag{9}$$

"Intent-to-treat" (ITT) estimator

The matching estimator of the average treatment effect for those offered the program will be given by:

$$\frac{1}{n}\sum_{j=1:j,i\in S_p}^{n}\{E(s_i|w_i = w_j - \tau, y_i = y_j + \tau) - s_j(w_j, y_j)\} \qquad (10)$$

where $s_j(w_j, y_j)$ denotes the school attendance decision of a household with characteristics (w_j, y_j). [1]

[1] Notice that the average can only be taken over the region of overlapping support S_p, which in this case is over the set of families j for which the values $w_j - \tau$ and $y_j + \tau$ lie within the observed support of w_i and y_i.

Matched outcomes $E(s_i|w_i = w_j - \tau, y_i = y_j + \tau)$ are estimated non-parametrically using a two dimensional kernel regression estimator.

$$E(s_i|w_i = w_j - \tau, y_i = y_j + \tau) = \frac{\sum_{j=1:j,i\in S_p}^{n} s_i K(\frac{w_i - w_0}{h_n^w}) K(\frac{y_i - y_0}{h_n^y}) 1(x_1 = x_0)}{\sum_{j=1:j,i\in S_p}^{n} K(\frac{w_i - w_0}{h_n^w}) K(\frac{y_i - y_0}{h_n^y}) 1(x_1 = x_0)} \quad (11)$$

where:

- $w_0 = w_j - \tau_j$ and $y_0 = y_j - \tau_j$,
- $K(.)$ denotes the kernel biweight function ($K(s) = \frac{15}{16}(s^2 - 1)^2 \text{if} |s| \leq 1$), and
- h_n^w and h_n^y are the smoothing (or bandwidth) parameters.

Take-up Rates

The coverage rate - the probability that a family sends their child to school when the subsidy program is in place,

$$Pr(s(w-\tau, y+\tau)=1) = E(s(w-\tau, y+\tau)) \qquad (12)$$

This probability can be estimated using a non-parametric regression of the indicator variable s on w and y using only the sample with overlapping, evaluated at the points $w-\tau$, $y+\tau$

Average Impact Effect on the Treated

With estimates of the ITT and the TR estimate, it is easy to obtain an estimate of the ATT,

$$ATT(w,y) = \frac{ITT(w,y)}{E(s(w-\tau, y+\tau))} \tag{13}$$

Empirically, this is simply done by simply averaging over the ATE estimates for each individual families within the support region:

$$\frac{1}{n} \sum_{j=1:j,i \in S_p}^{n} \frac{E(s_i | w_i = w_j - \tau, y_i = y_j + \tau) - s_j(w_j, y_j)}{E(s_i | w_i = w_j - \tau, y_i = y_j + \tau)} \tag{14}$$

$$\max_{(s^1,s^2)} \quad U(c, s^1, ...s^n\mu) \tag{15}$$

$$\text{s.t.:} \quad c = (y + n\tau) + (w - \tau)\sum_{i=1}^{n}(1 - s^i)$$

$$ln(w) = \mu_w + \epsilon \tag{16}$$

Data

Fundacion ARU's set of harmonized household surveys.
It is important to note that set of harmonized household surveys has

- used a uniform definition of variables and indicators - to the extent that it is possible,
- restrained from using any kind of imputation or adjusting method and,
- (most importantly) corrected differences in sample design between different surveys constructing new sample weights using post-stratification methods

Evolution of School Attendance by Age

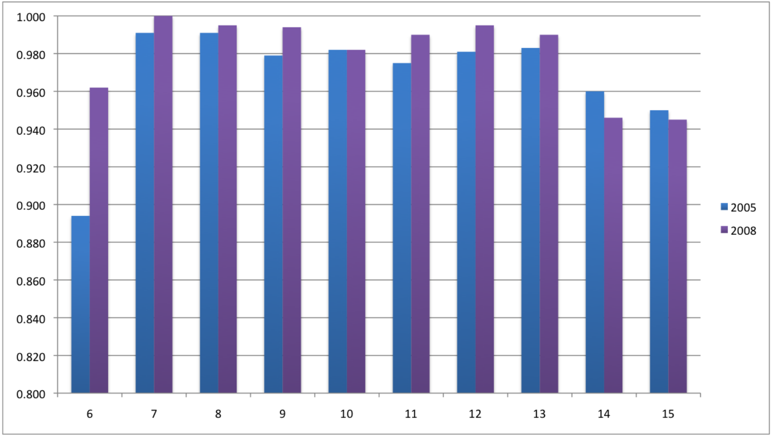

Figure: School Attendance Rates

Table: Predictions of the Impact of BJP (Ex-ante sample)

	Panel A. Boys		
Ages	Sample Size	% Overlapping	Effect
6	175	85	0.062 ***
7	233	89	0.040 **
8	216	92	0.019 *
9	209	95	0.001
10	202	93	0.002
11	210	91	0.003
12	218	94	-0.005
13	207	89	0.025
14	199	87	-0.003
15	208	83	0.003

Table: Predictions of the Impact of BJP (Ex-ante sample)

		Panel B. Girls	
Ages	Sample Size	% Overlapping	Effect
6	211	87	0.082 ***
7	213	84	0.061 **
8	200	89	0.033 **
9	207	95	0.001
10	218	94	0.001
11	181	93	0.005
12	216	92	-0.005
13	188	91	0.001
14	207	89	0.024
15	220	82	-0.009

Table: Predictions of the Impact of BJP (Ex-ante sample)

	Panel C. Boys and Girls		
Ages	Sample Size	% Overlapping	Effect
6	386	86	0.073 ***
7	446	87	0.050 **
8	416	91	0.026 **
9	416	95	0.001
10	420	94	0.002
11	391	92	0.004
12	434	93	-0.005
13	395	90	0.014
14	406	88	0.011
15	428	83	-0.003

Table: Predictions of the Impact of BJP (Ex-post sample)

	Panel A. Boys		
Ages	Sample Size	% Overlapping	Effect
6	168	83	0.050 ***
7	172	86	0.024 **
8	191	82	0.018 *
9	170	92	0.001
10	180	94	0.000
11	154	87	0.005
12	195	94	-0.004
13	175	91	0.003
14	191	90	0.005
15	184	86	0.007

Table: Predictions of the Impact of BJP (Ex-post sample)

	Panel B. Girls		
Ages	Sample Size	% Overlapping	Effect
6	167	86	0.060 ***
7	159	88	0.040 **
8	210	89	0.020 **
9	168	84	-0.001
10	190	90	0.002
11	205	94	0.003
12	171	92	0.005
13	187	86	0.025
14	185	95	0.003
15	160	89	0.003

Table: Predictions of the Impact of BJP (Ex-post sample)

	Panel C. Boys and Girls		
Ages	Sample Size	% Overlapping	Effect
6	335	85	0.055 ***
7	331	87	0.032 **
8	401	86	0.019 **
9	338	88	0.000
10	370	92	0.001
11	359	91	0.004
12	366	93	0.000
13	362	89	0.014
14	376	93	0.004
15	344	88	0.005

- Both ex-ante and ex-post predictions suggest that BJP has been successful increasing school attendance only for 6 to 8 years old children, and particularly for girls.
- All remaining ages show no effect on the school attendance of both, boys and girls.
- Similar patters of ex-ante and ex-post predictions can be interpreted as a sign of the robustness of the method.
- BJP has only encourage households to enroll children to school at the proper age but has not give an additional incentive to attend to those already enrolled.

Thank you.