The Effect of Participation in Public Childcare Centers: Evidence from Chile

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Why?

LA is among the regions with most progress in EC education.

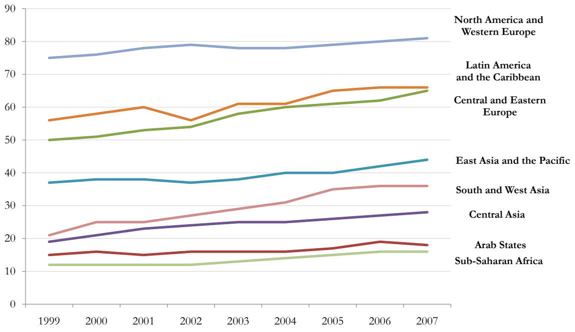
> *"The main question for education policymakers today is not so much whether investments should be made in early education, but how to invest so that programs will be effective in producing benefits, yet also be efficient and affordable" (IADB, 1999).*

Key Issues

- The field of economics has recently played a prominent role in providing science-based guidance on early childhood education (ECE) policy
- Salient economic arguments according to literature:
  - Ability gaps in cognitive and noncognitive skills emerge at early ages and persist
  - Strong multiplier effect of investment in early childhood
  - Public policy that promotes fairness and social justice while promoting productivity in the economy and society

Background

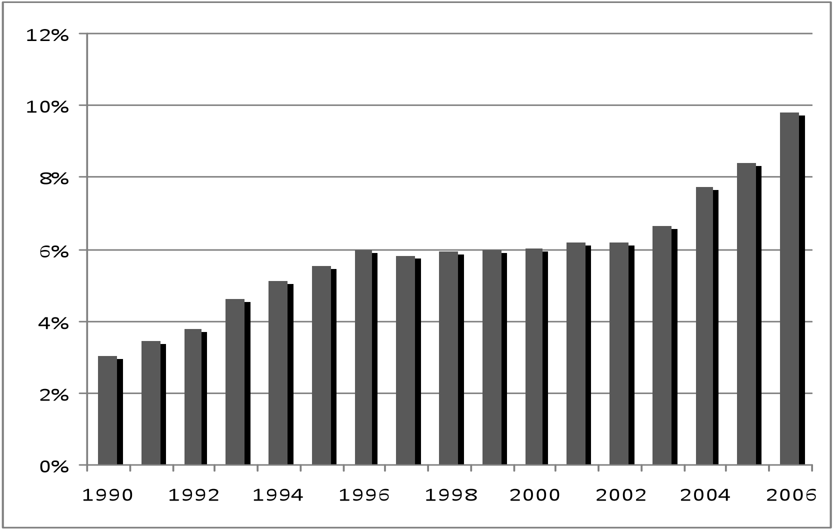
- Efforts to secure the quality of ECE programs have not accompanied the growing levels of preschool enrollment rates



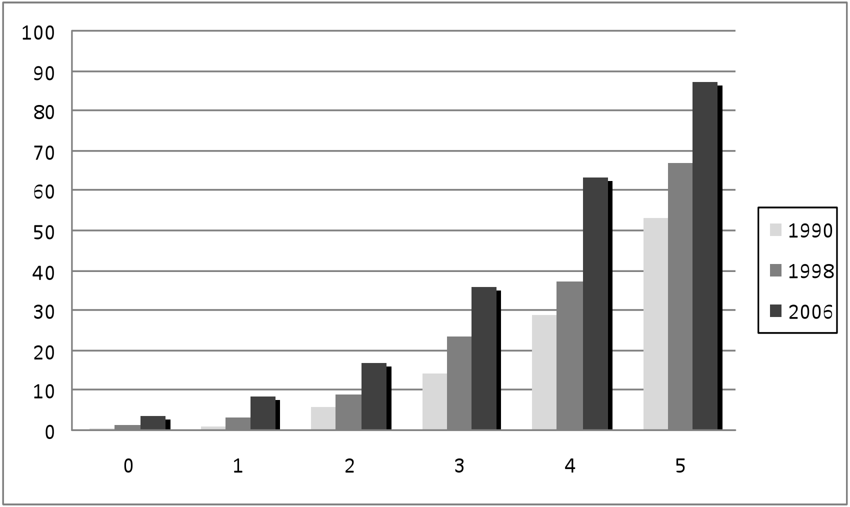
Why Chile?

- Chile has taken serious steps to improve the situation of young children, particularly the most vulnerable.
- National ECE policy established in 2006 (Chile Growths with You/Chile Crece Contigo)
    - Unfortunately the program has not been evaluated (multiple efforts)
    - Underlying logic: Increase on female participation rate and poverty reduction
    - All children benefit from this policy?
- Coverage by public providers nearly tripled between 2005-2007 and continue increasing (500% between 2006-2009). Quality?

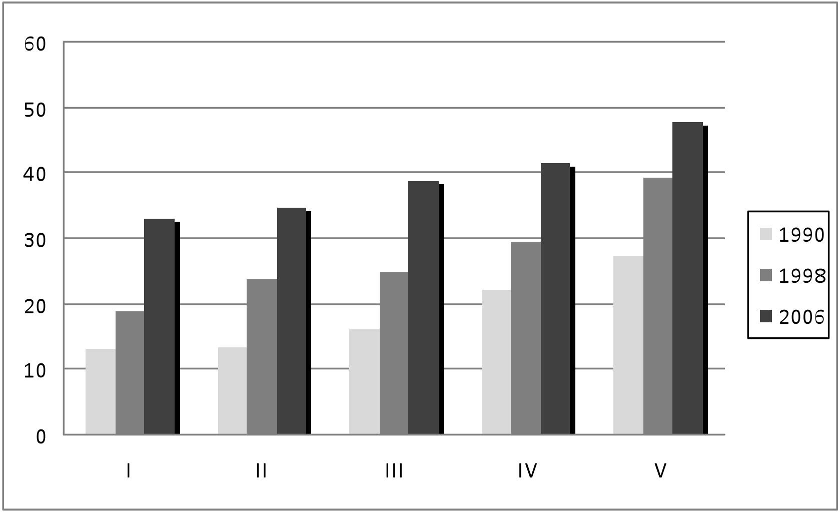
2A. As % of Total Public Expenditure in Education



3B. Enrollment by Age



3A. Enrollment by Income Quintiles



This Paper

- It presents a comprehensive empirical analysis of the effect of attending public childcare centers on cognitive and socioemotional dimensions.
- We allow for heterogeneous treatment effects and endogenous selection
- We employ a unique quasi-experimental longitudinal data and administrative records on the local availability of public child care centers.
- New NIH grant will help us to improve the analysis.

Our Results

- **Selection**: We show the importance of controlling for selection. We show that selection bias drives magnitude and significance behind IV and OLS.
- **Supply**: We find a significant role of supply-side variables as determinant of enrollment.
- **Impact**: Our results reveal small gains in different areas of child development, particularly this concerning motor and cognitive skills.
- **Impact**: Positive effects are concentrated among children aged 7 and 12 months.

The JUNJI Longitudinal Study (JLS)

Study comissioned by JUNJI in 2007 followed a quasi-experimental approach:

- Random sample of 41 public childcare centers
- Treatment group: randomly selected from children, 5-14 months, attending a public childcare center in April 2007 (N=331)
- Control group: randomly selected from healthy children who did not attend any childcare center but attended nearby health clinic (N=151)
- The purpose was to match socioeconomic conditions across groups (roughly the same age)

The JUNJI Longitudinal Study (JLS)

JLS contains rich data on child and family characteristics:

- Parental presence, age, education, and occupation
- Child birthweight, age, gender, and test scores obtained on the Battelle Developmental Inventory Test (BDIT)

Measures outcomes on the BDIT during April 2007 (baseline) and November 2007 (follow-up):

- 9 subdomains: Gross and fine motor skills, receptive and expressive communication, memory, reasoning, adult interaction, feeling expression, and eating
- Age-adjusted and subdomain-specific standardized test scores called T scores ($\mu = 50, \sigma = 10$) which we convert to Z scores ($\mu = 0, \sigma = 1$)

Table 1. Family Characteristics in the JLS Dataset, by Treatment Status

Variable	Control Group		Treatment Group		Mean Difference
	Mean	SD	Mean	SD	
	(1)	(2)	(3)	(4)	(5)
Mother's Presence	0.99	0.08	0.99	0.08	0.00
Mother's Education	10.92	2.54	10.98	2.77	-0.06
Mother's Age					
18 years or less	0.12	0.33	0.08	0.27	0.04
19-25 years	0.46	0.50	0.34	0.47	0.12*
26-35 years	0.32	0.47	0.40	0.49	-0.07
36 years or more	0.10	0.30	0.18	0.39	-0.08*
Mother's Job					
Out of the labor force	0.65	0.48	0.23	0.42	0.42*
Unemployed	0.07	0.25	0.10	0.30	-0.04
Unstable job	0.12	0.33	0.17	0.38	-0.05
Stable job	0.16	0.37	0.49	0.50	-0.33*
Father's Presence	0.72	0.45	0.57	0.50	0.14*
Father's Education	10.99	3.07	11.07	2.49	-0.08
Father's Job					
Out of the labor force	0.00	0.00	0.01	0.10	-0.01
Unemployed	0.02	0.14	0.05	0.22	-0.03
Unstable job	0.18	0.38	0.13	0.33	0.05
Stable job	0.81	0.40	0.81	0.39	0.00
Number of Observations	151		331		

* denotes rejection of the equality of means with greater than 95% confidence

Representativity

- Quasi-experimental approach raises doubts about external validity
- Use nationally representative survey (CASEN 2006) and compare family characteristics across datasets
- Mean values are highly comparable across the datasets
- Reasonably confident of the representativeness of our results

Framework

- Model of self-selection into public childcare centers.
- At $t = 0$, parents decide whether or not to enroll their child i in a public childcare center, and we observe the first set of developmental outcomes.
- At $t = 1$, the enrollment decision remains the same and we observe the second developmental outcomes of the child.

Framework

- Let D_i^0 denote a binary decision variable such that,

$$D_i^0 = \begin{cases} 1 & \text{if family sends child } i \text{ to a public childcare center} \\ 0 & \text{if family does not send child } i \text{ to } \textit{any} \text{ childcare center} \end{cases}$$

- Standard choice model:

$$D_i^0 = 1[I_i^0 \geq 0] \tag{1}$$

where $I_i^0 = Z_i^0\gamma - V_i^0$ and Z_i^0 denotes a vector of observable components, which is independent from V_i^0.

Framework

- Y_{1i}^t (Y_{0i}^t) as a vector of outcomes associated with child i in the event of attending (not attending) the public childcare center at time t.
- Due to the data limitations, we use a contemporaneous production function model:

$$Y_{1i}^t = \alpha_1^t + X_i^t \beta_1^t + \epsilon_{1i}^t \quad (2)$$
$$Y_{0i}^t = \alpha_0^t + X_i^t \beta_0^t + \epsilon_{0i}^t \quad (3)$$

where X_i^t represents a vector of observable, β_1^t and β_0^t are the parameters, and $(\epsilon_{0i}^t, \epsilon_{1i}^t)$ represent the unobservable components which influence the developmental outcomes of child i in period t.

Framework

- Thus, we allow the unobserved components from outcomes and parents' choices to be correlated.
- Potential sample selection problems.
- Although Z_i^0 and X_i^t can share elements, they are fundamentally different objects.

Framework

- At time t the researcher observes,

  $$Y_i^t = (D_i^0) Y_{1i}^t + (1 - D_i^0) Y_{0i}^t$$

  which under the contemporaneous specification becomes,

  $$Y_i^t = \alpha_0^t + (\alpha_1^t - \alpha_0^t) D_i^0 + X_i^t(\beta_1^t - \beta_0^t) D_i^0 + X_i^t \beta_0^t + \nu_i^t \quad (4)$$

  where ν_i^t is the error term on the regression and equals $\epsilon_{0i}^t + (\epsilon_{1i}^t - \epsilon_{0i}^t) D_i^0$.
- Interpreting OLS or IV results might be a challenge.

Selection in Levels and Gains and the Treatment Effect

- There are two sources of potential selection bias
  1. Standard selection bias from the correlation between ϵ_{0i}^{t} and D_i^0 (i.e. selection in levels).
  2. From the presence of D_i^0 in ν_i^t (i.e. selection based on gains). (Heckman, Urzua and Vytlacil, 2006)
- Our approach addresses these two issues of selection.

Treatment Effect

- The individual treatment effect in period t can be represented as,

$$Y_{1i}^t - Y_{0i}^t = (\alpha_1^t - \alpha_0^t) + X_i^t(\beta_1^t - \beta_0^t) + (\epsilon_{1i}^t - \epsilon_{0i}^t)$$

- In period t we can define the average effect of the treatment on a child drawn randomly from a population of individuals with observable characteristics X:

$$\begin{aligned} ATE^t(X) &= E(Y_{1i}^t - Y_{0i}^t | X_i^t) && (5) \\ &= (\alpha_1^t - \alpha_0^t) + X_i^t(\beta_1^t - \beta_0^t) && (6) \end{aligned}$$

- Since we are interested on the dynamic effects, we define the incremental average treatment effect as,

$$\Delta ATE(X) = ATE^t(X) - ATE^{t-1}(X) \qquad (7)$$

Empirical Model

Consider the following linear model for the development outcomes of child i:

$$Y_i^t = \gamma_0^t + \gamma_1^t D_i + \gamma_2^t D_i \cdot Age_i^t + \gamma_3^t D_i \cdot (Age_i^t)^2 + X_i \gamma_4^t + \nu_i^t$$

Focus on estimating the average treatment effect as a function of observable characteristics, i.e., $ATE^t(X)$

- OLS does not identify $ATE^t(X)$ in the presence of selection
- IV accounts only for selection in levels, but does not generate $ATE^t(X)$
- CF approach accounts for selection in levels *and* gains.

Control Function Approach

Assuming joint normality of the error terms, estimate $ATE^t(X)$ using a CF approach:

$$\begin{aligned} Y_i^t &= \gamma_0^t + \gamma_1^t P_i + \gamma_2^t P_i \cdot Age_i^t + \gamma_3^t P_i \cdot (Age_i^t)^2 \\ &\quad + X_i \gamma_4^t + \gamma_5^t \phi(\Phi^{-1}(P_i)) + \eta_i^t \end{aligned}$$

$\Delta ATE(X)$ differences this equation for each t across treatment and control and then differences across periods. P_i represents the propensity score.

Exclusion Restrictions

Our exclusion restrictions capture the plausibly exogeneous growth in the supply of public childcare centers:

- We use administrative records provided by JUNJI
- We compute:
  - The growth in the number of public childcare centers
  - The growth in capacity spots at these centers
- Growth is computed at the municipality-level and measures the change over a variable period of time:
  - Starting at the time of the child's month of birth (Jan - Dec 2006)
  - Ending at the time of the child's enrollment in the JLS childcare center (Apr 2007)

Exclusion Restrictions

We argue that we have valid exclusion restrictions/IVs:

- Do not expect aggregate level measures of childcare supply to be linked to individual variables
- Use lagged measures of childcare supply
- Evidence that our IVs are exogeneous from socioeconomic characteristics at the municipality level
- Growth in supply was not driven by a systematic allocation rule rather it was driven mainly by center renovations
- Similar IVs can be found in the literature. See Berlinski et al. (2008), Bernal et al. (2009), and Loeb et al. (2007)

Table 4. Propensity Score Estimation for Attending a JLS Center, Probit Marginal Effects

Variables	**Attends JLS Center**
Δ Number of centers	0.0695*
	(0.0399)
Δ Capacity spots	-0.00509***
	(0.00183)
Child's Age at $t = 0$ (months)	0.0252***
	(0.00870)
Child's Birthweight (grams)	0.0000181
	(0.0000368)
Mother's Age: < 18	-0.156
	(0.118)
Mother's Age: 19-25	-0.188***
	(0.0726)
Father's Education (years)	0.00137
	(0.0120)

Robust standard errors clustered by municipality in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The Demand for Childcare

- Positive determinants:
  - # of public childcare centers within municipality
  - child's age at time of entry into public childcare
  - mother's employment (increasing in job stability)
- Negative determinants:
  - # of capacity spots at public childcare centers within municipality
  - mother's age in the early 20s
  - missing father
  - father's employment (increasing in job stability)

Testing for Selection

- Find evidence of selection.
- Children who select into treatment experience lower marginal returns compared to children who do not select into treatment
- Imperative to account for sources of selection bias

Figure 1. Average Treatment Effects Relative to OLS and IV Bias, by Period

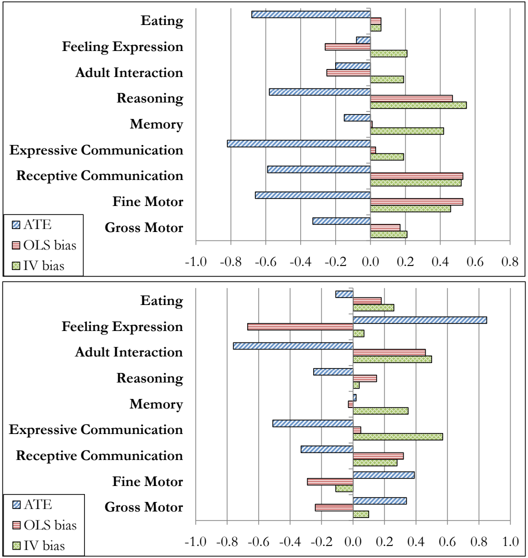
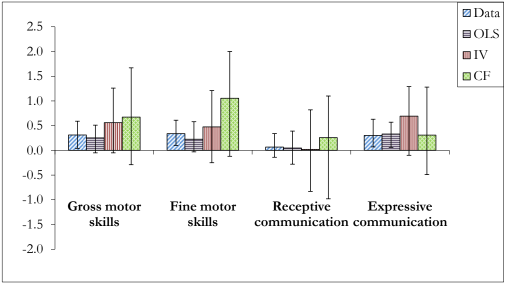
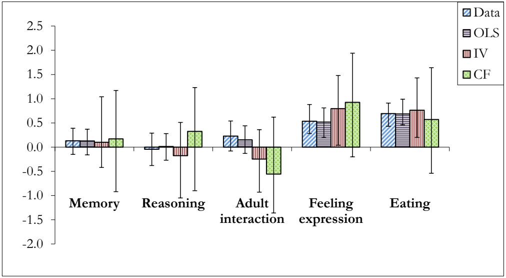


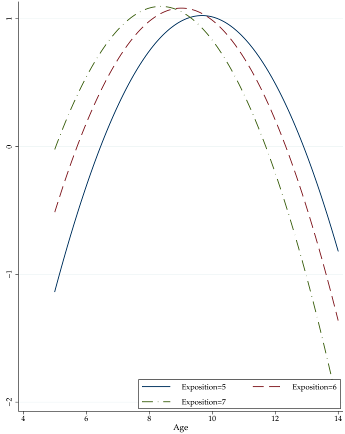
Figure 2. Dynamic Treatment Effects on Child Development Outcomes, by Model Type





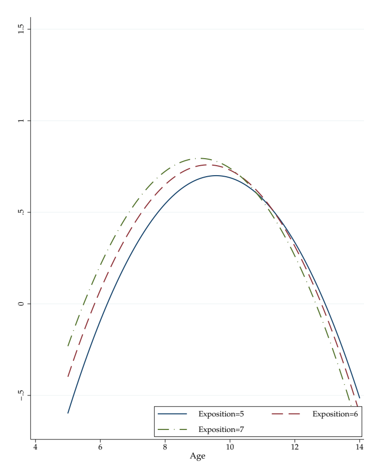
Age-Specific Effects

Figure 3a. Age-Specific ΔATE for the Subdomain of Reasoning



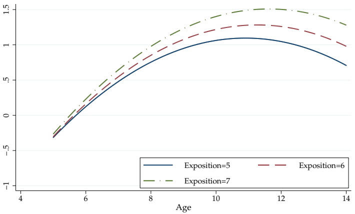
Age-Specific Effects

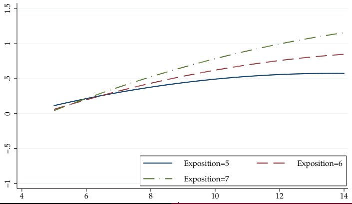
Figure 3b. Age-Specific ΔATE for the Subdomain of Expressive Communication



Age-Specific Effects

Figure 4. Age-Specific ΔATE for the Subdomains of Feeling Expression and Eating





Conclusions

- Static effects of the program on child development outcomes are mostly negative
- Incremental effects are generally positive, particularly in the areas of motor and cognitive skills
- Adult interaction skills are negatively affected by the program
- Effects tend to behave as concave functions of child's age and depend highly on the length of program exposure
- Controlling for sources of selection bias, we find that gains are underestimated using conventional regression models
- (Not today: We find that incremental TT is larger than incremental ATE except for adult interaction, expressive communication and eating...peer effects?).

Brief Overview of Treatment on the Treated

- Knowledge of $ATE^t(X)$ and the selection mechanism involved allows us to gain insight $TT^t(X)$ and $\Delta TT(X)$

$$\begin{aligned} TT^t(X) &= E(Y_{1i}^t - Y_{0i}^t | X_i^t, D_i = 1) \\ &= \underbrace{E(Y_{1i}^t - Y_{0i}^t | X_i^t)}_{\text{ATE}} + \underbrace{E(\epsilon_{1i}^t - \epsilon_{0i}^t | D_i = 1)}_{\text{Sorting gain}} \end{aligned}$$

- $\Delta TT(X)$ reinforces $\Delta ATE(X)$ in most dimensions
- $\Delta TT(X)$ is lower relative to $\Delta ATE(X)$ for the subdomains of adult interaction, expressive communication, and eating
- Relevance of peer effects in public childcare center given negative sorting mechanism

Results in the Literature

Behrman et al. (2004) evaluate the Bolivian PIDI program:

- Statistically significant and positive average marginal effects on motor skills, psychosocial skills, and language acquisition
- Mainly for children > 37 months of age who participated for ≥ 7 months
- Impacts are cumulative, greater impacts associated with longer program exposure, particularly ≥ 1 yr
- For children ages 6-24 months most effects are positive but insignificant, especially if treatment duration is < 1 yr

Results in the Literature

Bernal et al. (2009) evaluate the Colombian HCBF program:

- Positive but insignificant effects on child cognitive and psychosocial skills
- Mainly for children aged 36-48 months with 5-15 months of program exposure
- Independent of age, short-term and medium-term positive and significant effects on children with $\geq$ 16 months of exposure

Overall Findings

- Average effect of attending a public childcare centers is initially negative but over time becomes positive for nearly all areas of child development
  - Gains most evident in the areas of motor and cognitive skills
  - Effects concentrated among children ages 7-12 mnths participating for longest time (7 mths)
  - Negative impacts on adult interaction, may be related to the low quality of individual care provided by a limited staff

Policy Implications

- Attending a public childcare center in Chile may enhance child development
- Lack of age-appropriate activities for the younger and older may yield benefits only for middle age group
- Negative social behaviors may potentially undermine the benefits of center-based care, especially among very young children
- Inadequate quantity and quality of educators may also produce detrimental effects

Concluding Thought

Future challenge:
Expand ECE coverage, particularly for the younger and economically disadvantaged children in the population, while maintaining and continually improving the quality of services provided, considering the higher level of expenditure associated with creating an age-appropriate curriculum and providing an adequate number of trained teaching staff