

Improving Early-Childhood Human Development: Experimental Evidence from India

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- Developing countries have made **impressive progress in improving school enrollment and completion** in the last two decades.
- However, student **learning levels** in these settings **are very low**.
 - 2017 National Achievement Survey: 1 in 3 third-graders cannot read texts and 1 in 2 cannot use math to solve problems (NCERT 2018).
 - 2018 Annual Status of Education Report: 43% of first-graders cannot recognize letters and 36% cannot recognize numbers (ASER 2019).
- One promising option for alleviating this problem is **better early-childhood education (ECE)**.
 - The expansion of education in developing countries has typically focused on school education.
 - Yet, if the productivity of resources in school education is constrained by low school readiness, the returns to ECE may be high.
- Despite **growing policy interest**, there is **little high-quality evidence** on cost-effective ways to **improve ECE at scale**.

- We present **experimental evidence** on the **largest ECE program in the world**: the Integrated Childhood Development Scheme (ICDS).
 - It serves over 36 million 3- to 6-year-olds for **free**, disproportionately **catering to the poor**.
 - It provides a range of early-childhood **health and nutrition services**, in addition to **pre-school education**.
 - It does so through 1.35m **anganwadi centers** (AWCs), staffed with:
 - ① an *anganwadi* worker (AWW), responsible for **health and education services**; and
 - ② an *anganwadi* helper (AWH), responsible for **preparing meals, feeding children, and cleaning the AWCs**. AWC picture
- Despite its importance, ICDS has **limited staffing and funding**.
 - In particular, the **multiple responsibilities** assigned to the AWW limit the time she can devote to **pre-school education**.
- Further, **AWW salaries are much lower** than those of civil-service teachers.

Intervention

- We evaluated the effect of **hiring a worker** exclusively devoted to **teaching pre-school education** in the state of **Tamil Nadu**.
- The Government of Tamil Nadu (GoTN) offered treatment AWCs a **one-time grant** to hire an **Early Childhood Care and Education (ECCE) facilitator** to assist the AWW with pre-school education.
 - Facilitators were hired on **two-year contracts**.
 - Eligibility criteria resembled those for AWWs. Facilitators had to:
 - 1 be **female**;
 - 2 be at least **18 years old**;
 - 3 reside in the **local community** (hamlet, ward, or village); and
 - 4 have passed **grade 10** board exams.
 - GoTN had already developed an **ECCE curriculum** with UNICEF, which included daily activities recommended for each day.
 - It also developed **manuals** and **trained** facilitators on their expected division of labor (with AWWs) each year.
 - Facilitators were required to log their daily activities on a register.

Experiment

- We drew a random, proportional-to-size (PPS) sample of **320 AWCs across four rural districts**. Sampled districts map
- We randomly assigned:
 - ① 160 AWCs to receive a Early Childhood Care and Education (ECCE) facilitator, paid half the salary of an AWW (“treatment” group); and
 - ② 160 AWCs to not receive it (“control” group).
- We stratified our randomization by **district**, whether the AWC had a **vacant AWW position**, and **local demographics** (e.g., population, language, age and occupation distribution, and family income).
- Control and treatment AWCs, AWWs and children were **comparable at baseline**. Comparison of AWCs Comparison of AWWs Comparison of children
- The combination of a **representative sample** and **government implementation** extends the validity of our results to the entire state (as described in Muralidharan & Niehaus 2017).

- We collected four types of data:
 - 1 **Child assessments** of math, language, and executive function skills.
 - Baseline (Sep-Oct 2016) and endline (Mar-Apr 2018). **Distributions**
 - Administered individually, orally, and in the local language (Tamil).
 - At endline, children were assessed at the centers and households.
 - 2 **Weight and height** of children.
 - Baseline (Sep-Oct 2016) and endline (Mar-Apr 2018).
 - At endline, children were measured at the centers and households.
 - 3 **Surveys of implementation fidelity.**
 - Six months (Apr-May 2017) and a year (Nov 2017) after rollout.
 - Checked ECCE facilitators were hired, paid on time, and focused on pre-school education.
 - 4 **Unannounced visits** and **announced observations** of instruction.
 - Visits during the year (Feb 2018) in 160 randomly-selected AWCs.
 - Tracked share of time allotted to different tasks while AWC was open.
 - Observations during the year (Feb 2018) in 80 randomly-selected AWCs.
 - Tracked share of time devoted to instruction, class management, or being off task during pre-school education time (10am to 12pm).

Empirical strategy

- We estimate the impact of the intervention by **comparing the instructor and child outcomes** of control and treatment centers:

$$Y_{ic} = \alpha_{s(c)} + X'_{ic}\gamma + \beta D_c + \varepsilon_{ic}, \quad (1)$$

- Y_{ic} is an outcome for child i enrolled at *anganwadi* center c ;
 - $\alpha_{s(c)}$ is the randomization-stratum fixed effect;
 - X_{ic} is a vector of baseline covariates that includes a measure of the outcome variable for individual students, the mean outcome for all students at the center, and AWW education and experience; and
 - D_c is an indicator variable for assignment to the treatment group.
- We estimated the impact on **two samples**: children assessed in the AWC and at their homes. Attrition by exp. group Attrition by covariates
 - Follow-up rates: AWC 33% and HH 89%.

Results: Implementation fidelity

- The intervention was **well-implemented**:
 - Virtually all treatment AWCs **hired an ECCE facilitator**.
 - By the first round of process monitoring (five months after GoTN issued a notification to treatment AWCs to hire the ECCE facilitator), 98% of centers had a facilitator.
 - The average facilitator was hired within 15-30 days of the notification.
 - Nearly all (97%) facilitators received the required **initial training**.
 - The average facilitator received 6 days of training.
 - The vast majority (79%) of facilitators had an **activities register**.
 - Similarly, 71% had an updated activities register.
 - Facilitators were **expected to work half the hours** of an AWW, and were correspondingly **paid around half the salary** (INR 4,000 or USD 59/month compared to INR 8,000 or USD 118/month for an AWW).

Impacts: Worker attendance and punctuality

The intervention had a **statistically insignificant effect on AWWs' absence**, but ECCE facilitators were less likely to be absent than AWWs.

Table: Impact on attendance and punctuality (unannounced visits)

	(1)	(2)	(3)	(4)	(5)
	AWWs		Impact on AWWs	ECCE facilitators	Diff. btw. workers
	Control	Treatment	Col. (2)-(1)	Treatment	Col. (4)-(2)
Arrived by AWC opening time (9am)	.125 (.333)	.237 (.428)	.081 [.07]	.213 (.412)	-.025 [.058]
Arrived by PSE start time (10am)	.6 (.493)	.613 (.49)	-.013 [.08]	.8 (.403)	.188** [.079]
Absent	.263 (.443)	.338 (.476)	.09 [.074]	.138 (.347)	-.2*** [.075]
N (centers)	80	80	160	80	160

Notes: (1) This table compares the attendance and punctuality of AWWs in control and treatment AWCs and of AWWs and ECCE facilitators in treatment AWCs, based on unannounced visits about a year after the rollout of the intervention (Feb 2018). The visits were conducted from 10am to 12pm during the time officially designated for pre-school education. Columns may not add up to 120 minutes due to late arrivals, absences, and early departures from the AWC. (2) * significant at 10%; ** significant at 5%; *** significant at 1%.

Impact on AWC opening time

Impacts: Worker time allocation

AWWs devoted shifted time away from pre-school instruction and onto other tasks, resulting in an overall **doubling of time on education** and a **near-tripling of time on nutrition**.

Table: Impact on time allocation (unannounced visits)

	(1) AWWs		(3) Impact on AWWs	(4) ECCE facilitators	(5) Diff. btw. workers	(6) AWWs & facilitators	(7) Impact on AWCs
Minutes per day on...	Control	Treatment	Col. (2)-(1)	Treatment	Col. (4)-(2)	Col. (2)+(4)	Col. (6)-(1)
...pre-school education	38.4 (29.665)	18.15 (21.432)	-18.731*** [4.278]	57.45 (31.53)	39.3*** [5.015]	75.6 (37.092)	38.439*** [5.816]
...administrative tasks	21.9 (22.084)	35.1 (26.715)	12.292*** [4.135]	19.65 (17.834)	-15.45*** [3.785]	54.75 (34.519)	30.439*** [4.816]
...health and nutrition tasks	5.7 (9.917)	10.8 (14.616)	4.474** [1.904]	5.55 (8.527)	-5.25*** [1.971]	16.35 (18.338)	9.813*** [2.257]
...off duty	37.5 (33.42)	51.45 (33.301)	13.018** [5.774]	32.85 (30.713)	-18.6*** [5.026]	84.3 (50.66)	46.222*** [7.967]
N (centers)	80	80	160	80	160	80	160

Notes: (1) This table compares the time allocation of AWWs in control and treatment AWCs and of AWWs and ECCE facilitators in treatment AWCs, based on unannounced visits about a year after the rollout of the intervention (Feb 2018). The visits were conducted from 10am to 12pm during the time officially designated for pre-school education. Columns may not add up to 120 minutes due to late arrivals, absences, and early departures from the AWC. (2) * significant at 10%; ** significant at 5%; *** significant at 1%.

Pre-school education time

Administrative time

Health and nutrition time

Time off duty

Impacts: Child learning outcomes

Children in treatment centers **outperformed** their control peers in **math and language** in both center- and household-based assessments.

Table: Impact on endline assessments (full sample)

	(1)	(2)	(3)	(4)
	Standardized scores			
	Math	Language	Executive function	Composite score
<i>A. AWC assessments</i>				
Treatment	0.290***	0.458***	0.179***	0.287***
	[0.061]	[0.080]	[0.052]	[0.058]
N (children)	1514	1514	1514	1514
<i>B. Household assessments</i>				
Treatment	0.129***	0.102**	0.054	0.110**
	[0.049]	[0.051]	[0.042]	[0.045]
N (children)	2080	2080	2080	2080

Notes: (1) The table shows the impact of the intervention on assessments of math, language, and executive function after two years. It displays results for all children who participated in the baseline and center- or household-based assessments. All specifications account for child scores and AWC mean scores at baseline (coefficients not shown). (2) Baseline scores are standardized with respect to the full sample at baseline. Endline scores are standardized with respect to the control group at endline. (3) * significant at 10%; ** significant at 5%; *** significant at 1%.

Impact on common sample

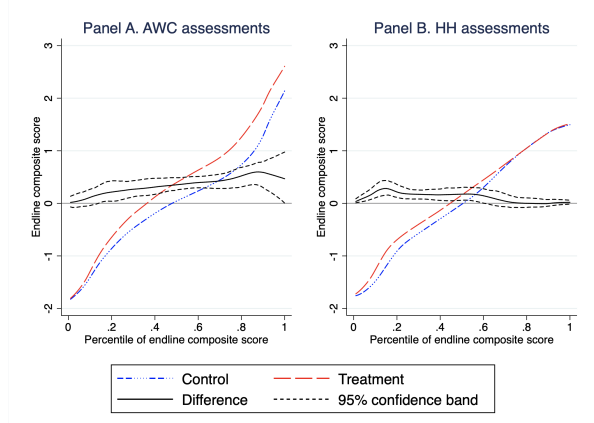
Heterogeneous effects (full sample)

Heterogeneous effects (common sample)

Impacts: Child learning outcomes

The treatment distribution first-order stochastically dominates the control group suggesting **broad-based test score gains from the program**.

Figure: Quantile treatment effects on endline assessments by percentile



Notes: The figure shows the standardized composite score on the endline assessments at each percentile of the endline assessment, by experimental group. It shows the difference between groups and the bootstrapped 95% confidence intervals. (2) It only includes children who were included in the baseline and the respective endline.

Impacts: Child nutrition

The intervention also improved children's weight and height.

Table: Impact on endline weight- and height-for-age (full sample)

	(1)	(2)	(3)	(4)	(5)	(6)
	WAZ score	Underweight (WAZ<-2)	Severely underweight (WAZ<-3)	HAZ score	Stunted (HAZ<-2)	Severely stunted (HAZ<-3)
<i>A. AWC measurements</i>						
Treatment	0.096*** [0.033]	-0.018 [0.017]	-0.031** [0.012]	0.093** [0.044]	-0.047** [0.022]	-0.024** [0.011]
N (children)	1538	1538	1538	1389	1389	1389
Control mean	-1.762	0.384	0.091	-1.492	0.291	0.057
<i>B. Household measurements</i>						
Treatment	0.044 [0.032]	-0.016 [0.018]	-0.007 [0.010]	0.009 [0.053]	-0.025 [0.017]	-0.009 [0.007]
N (children)	2053	2053	2053	2027	2027	2027
Control mean	-1.551	0.322	0.075	-1.162	0.203	0.040

Notes: (1) Columns 1-3 show the impact of the intervention on children's weight-for-age (WAZ) scores, the share of underweight children (i.e., those with WAZ scores below -2), and the share of severely underweight children (i.e., those with WAZ scores below -3). All specifications account for WAZ scores at baseline (coefficients not shown). Columns 4-6 show the impact of the intervention on children's height-for-age (HAZ) scores, the share of stunted children (i.e., those with HAZ scores below -2), and the share of severely stunted children (i.e., those with HAZ scores below -3). (2) * significant at 10%; ** significant at 5%; *** significant at 1%.

Impact on common sample

Quantile treatment effects on WAZ

Quantile treatment effects on HAZ

Cost effectiveness: Calculations

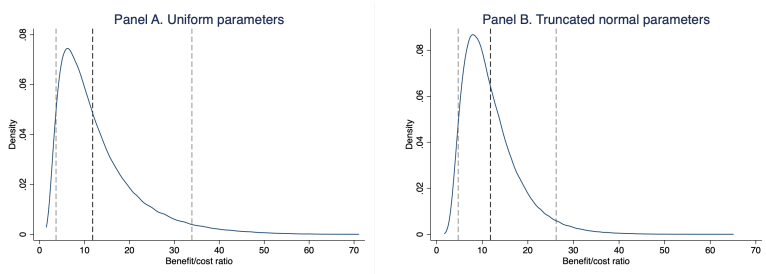
Table: Cost/benefit calculations for ECCE facilitator

(1) Parameter	(2) Source	(3) Value
<i>A. Projecting future earnings</i>		
Labor force participation rate	LFP for rural population of TN aged 15+, 2011-2012 NSS	.52
Current average daily wage	Average wage for rural workers aged 15+, 2011-2012 NSS	268
Days worked per year when in labor force	Assumption	250
Current annual earnings when in labor force	Calculation	67,000
Annual real wage growth	Assumption	.05
Discount rate	Assumption	.03
Average discounted PDV of lifetime earnings	Calculation	3,311,001
<i>B. Experimental impacts</i>		
Treatment effect (std.)	Experimental estimate	.110
Proportional earnings gain per std. dev.	Literature estimates linking test scores to earnings	.13
Predicted PDV earnings gain per child	Calculation	47,347
<i>C. Benefit/cost ratio</i>		
Children per center	Experimental data	14
Cohort adjustment factor	Assumption	1.33
Predicted benefit per center	Calculation	881,607
Program cost per center	Government order	74,478
Benefit/cost ratio	Calculation	11.8

Notes: This table reports a cost benefit analysis of the intervention based on projected impacts on adult earnings. Column (1) lists the parameters necessary to calculate costs and benefits, and column (2) describes the source used for each parameter, with details given in footnotes. Panel A lists the parameters necessary to project the present discounted value (PDV) of lifetime earnings for Tamil Nadu. Panel B lists parameters and assumptions necessary to predict the increase in earnings generated by the ECCE facilitator intervention for each child. Panel C combines this projection with program costs to produce a benefit/cost ratio.

Cost effectiveness: Sensitivity analysis

The benefit/cost ratio is large for nearly all parameter values we consider.



Notes: (1) This figure explores the sensitivity of the ECE facilitator benefit/cost ratio to parameter values. We obtain a distribution of benefit/cost ratios by drawing each parameter from a range of possible values, with the preferred values in the middle of each range. Days worked while in the labor market range from 225 to 275. The wage growth rate ranges from 3 percent to 7 percent. The discount rate ranges from 1.5 percent to 4.5 percent. The proportionate increase in earnings per standard deviation of test scores ranges from 7 percent to 19 percent. Panel A plots the distribution of ratios generated by drawing each parameter from an independent uniform distribution. Panel B plots a distribution generated by drawing each parameter from an independent truncated normal distribution centered at the middle of the range with standard deviation $1/4$ of the width of the range. Results come from fitting kernel densities to 500,000 draws in each panel. The mean and median ratios are 14.2 and 11.4 in panel A, and 13.1 and 11.6 in panel B. Gray lines indicate 5th and 95th percentiles in each panel (4.1 and 33.9 for panel A and 5.3 and 26.2 for panel B), and the black vertical line denotes our preferred estimate.

- Our most important contribution is to show that it is **possible to improve early childhood learning outcomes in a highly cost-effective way** using a government-implemented intervention.
 - We do so in the **world's largest early-childhood care program**.
 - ICDS (India): 36m+ children aged 3-6.
 - Head Start (U.S.): 650k funded places in 2019 (NHSA 2020).
 - This is also the **first RCT of an attempt to improve education outcomes in the ICDS** in India.
- We contribute to the **literature on interventions to improve ECE**.
 - Interventions for young children (e.g., home visitation) yielded large positive impacts at small scales, but modest/null effects at larger scale (Gertler et al. 2014; Attanasio et al. 2014).
 - We demonstrate **strengthening public systems** can improve outcomes at scale.
 - The estimated benefit/cost ratio is 12x. Even if increased incomes are captured as taxes, the return on public funds invested in the program would be infinite, since the government would more than recover its costs and there would still be large benefits accruing to citizens.

- Augmenting state capacity for service delivery through adding locally-hired staff may be a highly **cost-effective public investment**.
 - Low-income countries typically have a much lower ratio of public employees per citizen, in part because of **large civil-service wage premiums** (Finan et al. 2017)
 - This premium is **not correlated with productivity** (Muralidharan & Sundararaman 2011; Bau & Das 2017; de Ree et al. 2018).
 - Expanding hiring of **locally-hired staff at lower than civil-service salaries** may be a promising policy option (Muralidharan 2016).
- Our results speak to the literature on the costs and benefits of **occupational licensing** (Kleiner 2000).
 - Expansions of early-childhood education stipulate teachers should be qualified/trained (Berlinski & Schady 2015; DHHS 2017; Gol 2019).
 - Our results suggest that **such qualifications may not be necessary**, and that locally-hired staff, with a secondary school education, and just a week of training may be highly effective at improving ECE outcomes.
 - They are **consistent with those in school education** (Banerjee et al. 2007; Duflo et al. 2015; Muralidharan & Sundararaman 2013).

Many thanks

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