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Keywords
Midday meal, School Feeding, Learning, Health, India

JEL Codes
I21, I25, O12

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The Effects of the Indian Mid-Day Meal Scheme on Cognitive and Health Outcomes of Children in Andhra Pradesh

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Abstract

This paper analyses the impact of the Indian Mid-Day Meal Scheme on the health and cognitive outcomes of schooling children living in the Indian State of Andhra Pradesh. We exploit the variability derived from the individual educational history of children, combined with the phased implementation of the program targeting only students in the public sector, to construct a variable measuring the monthly cumulative exposure to the Mid-Day Scheme. We provide evidence of the positive impact of the policy on children attending public schools, particularly in reducing inequalities between children enrolled in the private and public sectors. Lastly, employing a Heckman Selection model accounting for the selection issue on the type of school attended by children, we show that the impact of the policy is positive and consistent regardless of the type of school attended.

Keynotes: Midday meal, School Feeding, Learning, Health, India

JEL Classification: I21, I25, O12

1. Introduction

Poorer children are the most vulnerable to malnutrition, a condition that can have severe impacts on their health, cognitive development, and educational outcomes. Malnutrition not only hinders children's physical and mental growth but also exacerbates social inequalities, leaving those from poor backgrounds behind. The lack of essential nutrients during critical development periods leads to permanent deficits that limit learning opportunities and future success, perpetuating the cycle of poverty.

Attanasio et al. (2020) highlight the crucial role of parental investments in promoting various aspects of child development. Factors such as household resources, the prices of essential goods, and the number of children in a family contribute to disparities in parental investment, which, in turn, exacerbate the wealth gap in children's development. When parents are constrained by a lack of resources, programs aimed at supporting child development can be essential in mitigating these inequalities and ensuring more equitable investment in children. In particular, when parental investment in children's development is insufficient, the role of the schooling system becomes crucial.

The aim of this research is to examine the impact of the Indian Mid-Day Meal Scheme (MDMS), one of the largest school feeding programs globally, on the health and cognitive outcomes of children attending public schools in Andhra Pradesh. Like other regions in India, Andhra Pradesh has living and schooling conditions that fall below the standards needed to ensure successful individual development. Despite recent improvements, India continues to struggle with high malnutrition rates, especially among children and women (WFP, 2023; FAO, 2023).

MDMS delivers a daily cooked meal to primary and upper primary students in public schools to support their nutritional needs and boost enrolment and attendance. This study evaluates the Scheme's effects on children's outcomes since its start in Andhra Pradesh in 2003, initially targeting grades I to V, and its expansion in 2008 to include grades VI to X. Utilizing data from the Young Lives Indian Dataset, we leverage the Scheme's design, focusing on public school students in specified grades and years, to determine if cumulative exposure to MDMS has enhanced health and cognitive outcomes and reduced disparities between children in public and private schools.

As reported by ASER, one of the most important Indian independent organisations monitoring the Indian schooling system in the rural areas of the country, public schooling children perform systematically worse than their private counterparts, thus suggesting a difference in the teaching effectiveness between different types of institutions (ASER, 2023). The rise of the private school sector, its increasing presence in India's educational landscape and its transformation to become more accessible to a larger segment of the population (low-cost private schools) have been major elements of discussion in the country. The expansion of private schooling and its use by the poor signals low performance of public schools and parents' perception that private schools offer a better quality than public education (Kingdon, 2007). Muralidharan and Kremer (2008) show that private schools are significantly more likely to exist in villages with a high mean level of teacher absence in public schools. In such a contest with a strong inequality in access to educational opportunities and outcomes, the role of a school feeding program can be crucial.

The Mid-Day Meal Scheme (MDMS) is designed to enhance the nutritional intake of public school children, potentially improving their health and cognitive outcomes. This can help reduce inequalities between students in private and public schools. There are three main channels through which MDMS operates. Firstly, by improving the overall nutritional intake of students, the scheme directly impacts children's health, assuming no redistribution of resources within the household. Secondly, by providing a cooked meal at school, MDMS aims to alleviate hunger during school hours, which can enhance students' concentration and effort levels, and reduce illness-related absenteeism. Lastly, the scheme encourages social interaction among children during shared meals, potentially amplifying peer effects.

Unlike prior studies, our research focuses on studying the impact of cumulative exposure to the Mid-Day Meal Scheme, measured in months, on students attending primary and upper-primary schools and high schools. The sample of children in our analysis, consisting of students ranging from 7 to almost 16 years of age, enables us to investigate the impact of the policy for a more extended period than the one usually considered in the literature. The results of our study demonstrate that the Mid-Day Meal Scheme has successfully improved public school children's health and cognitive outcomes and contributed to narrowing the existing gaps between children enrolled in private and public schools. Moreover, employing a Heckman Selection model accounting for parental choice on the type of school to enrol the child, we have examined whether the results obtained for the population of children attending public schools could be extended to the entire schooling population in the sample. Results display that the policy would produce a similar effect regardless of the type of school that children are attending, emphasising the importance of sustaining the nutritional intake of the entire Indian schooling population. Finally, we investigate whether the marginal impact of the Mid-Day Meal Scheme decreases with children's age by interacting the exposure in months to the MDMS with the age in months of children. Our findings confirm the hypothesis found in the literature that the impact of School Feeding Programs is the largest among younger students, underscoring the importance of early interventions for children's health and human capital accumulation.

The rest of the paper is organised as follows. Section 2 presents the relevant literature. Section 3 explains the data set, including the key outcome variables, as well as the construction of the Mid-Day Meal Scheme exposure variable. The empirical approach is presented in Section 4, while Section 5 reports the results. Concluding remarks appear in the last section.

2. Literature

Malnutrition and food insecurity in early childhood significantly harm children's health and cognitive development. Studies by Humphries et al. (2015) and Aurino et al. (2019) using the Young Lives dataset from four developing countries [1] show that children from food-insecure households have lower height-for-age and weaker cognitive abilities in vocabulary, reading, and math compared to those from food-secure families. This suggests that high-quality education alone cannot ensure good educational outcomes without addressing students' health. In settings with limited parental investment, schools are the ideal places to implement health and nutrition support policies for children. These programs are particularly crucial in poor rural communities with limited access to health services, especially when targeting children from the most disadvantaged families (Bundy et al., 2017).

The literature examining the effects of School Feeding Programs (SFP) and Nutritional Programs on children's health, cognitive and educational outcomes is extensive (Drake et al., 2017). Excellent reviews by Aurino and Giunti (2022), Alderman and Bundy (2012) and Jomaa et al. (2011) provide numerous examples of research from various developing countries that consistently show a positive impact of such policies on children's outcomes. Ensuring children's daily nutritional intake is beneficial for their overall development and is crucial for helping children from disadvantaged backgrounds catch up after experiencing early life disadvantages. Although the overall impact of School Feeding Programs is positive, the magnitude of the effect varies depending on the context of the analysis.

Ahmed (2004) studied a UN school meal program in Bangladesh, and Vermeersch and Kremer (2005) analyzed a similar program in South Africa. Both found positive effects on children's weight and body-mass index, but no significant impact on height-related health indicators. Fang and Zhu (2022) observed that children from low-socioeconomic households in rural China benefited most from a school meal program, with those exposed reporting better health in later years. Additionally, Gelli et al. (2019) noted that the impact of school meal programs on health

[1] Data from the Young Lives Dataset collecting information on children and their families in Ethiopia, India, Perù and Vietnam

outcomes in Ghana varied according to the gender of the children. In particular, the program's impact on height-for-age was greater for girls and children from poorer families, while the effect on weight-for-age was more significant for boys.

Several studies have already examined the impact of the Mid-Day Meal Scheme and other School Feeding Programs on Indian children's health and educational outcomes. On the health side, Afridi (2010) and Singh et al. (2014) described the Mid-Day Meal Scheme as a successful policy that increases children's nutritional intake and improves their health. Afridi (2010) found that in Madhya Pradesh, the transition from raw grain transfers to cooked meals under the scheme resulted in a 49% to 100% increase in children's daily nutrient intake, depending on the nutrient. Additionally, the scheme acts as a safety net during natural disasters. Singh et al. (2014) show that in Andhra Pradesh, the scheme mitigated the negative health impacts of natural disasters, particularly droughts, on children entering public primary school.

Identifying the channels through which School Feeding Programs impact children's cognitive and learning development is challenging. Unlike health conditions, where the link between policy and health status is direct, understanding educational and cognitive outcomes requires examining how these programs modify households' incentives for school participation and how improved health status affects cognitive children's outcomes. Improved nutritional intake can reduce hunger, enhancing pupils' concentration during lectures (Drèze and Khera, 2017; Drèze and Goyal, 2003). Better health can also decrease illnesses, reducing the days of absenteeism from school (Mostert, 2021). Many School Feeding Programs require regular school attendance to receive meals, potentially increasing time spent with peers and teachers. This conditionality may increase students' enrolment and participation rates by reducing the households' opportunity cost of schooling. While most research suggests a positive effect on enrolment and attendance rates (Kaur, 2021; Alderman et al., 2012; Khera, 2006; Ahmed, 2004; Vermeersch and Kremer, 2005), some studies report no impact (McEwan, 2013; for Chile) or limited impact for specific subgroups based on gender, religiosity or household's wealth (Afridi, 2011; Jayaraman and Simroth, 2011).

Among the studies finding a positive effect of School Feeding Programs on cognitive outcomes, Alderman et al. (2012) in Uganda and Mostert (2021) in South Africa find that such programs reduce grade repetition rates, particularly among boys. Vermeersch and Kremer (2005) demonstrate that the implementation of a School Feeding Program in Western Kenya improved learning outcomes only when experienced teachers were present. Similar results were found in Aurino et al. (2023) in Ghana, where boys and children living below the poverty line benefited the most from a School Feeding Program and Fang and Zhu (2022) in China, particularly among children from low socioeconomic backgrounds.

The Mid-Day Meal Scheme in India has also been shown to positively impact children's educational and cognitive outcomes. Afridi (2011) found in a randomized control trial in Madhya Pradesh that student attendance rates increased after implementing the policy, particularly for girls. This suggests that the impact of the Mid-Day Meal Scheme may vary by gender, influenced by traditional Indian norms and the higher opportunity cost parents assign to daughters attending school (Kingdon, 2007; Drèze and Kingdon, 2001). Jayaraman and Simroth (2011) also described how the enrolment rate increased due to MDMS, particularly for lower-caste children and those from low-income households. Kaur (2021) highlighted that this effect is more substantial for girls, almost twice that for boys. Regarding cognitive outcomes, Afridi et al. (2013) observed increased effort levels among pupils attending public schools in Delhi, suggesting that better-nourished children concentrate better at school; notably, the effect was greater for pupils attending schools with initially higher-than-average scores. Chakraborty and Jayaraman (2019), using cross-sectional observation of children in rural Indian students enrolled in public primary schools, provided evidence of a relationship between years of exposure to the MDMS and cognitive test scores.

Our research aims to contribute to the literature on the impact of School Feeding Programs on children's health and cognitive outcomes by analysing the effects of the Mid-Day Meal Scheme in the Indian State of Andhra Pradesh. We investigate whether the program can reduce inequality, particularly since it operates exclusively in public schools where students are generally more disadvantaged. Unlikely previous studies that focused solely on public primary school students (Chakraborty and Jayaraman, 2019; Singh et al., 2014), our research considers children aged 7 to almost 16, attending primary, upper primary schools and high schools. This broad age range allows us to investigate whether the effects of the MDMS diminish as children grow older. As King and Behrman (2009) noted, when evaluating a social program, it is crucial to identify the timing and the length of exposure to evaluate a policy's impact. Therefore, we explore if the Mid-Day Meal Scheme's effects vary with age to optimize its implementation and maximise benefits. Following Chakraborty and Jayaraman (2019), we analyse the impact of the MDMS using a cumulative exposure measure. However, instead of relying solely on age and grade information normally available in a cross-sectional setting, we calculate the total months of MDMS exposure using each child's educational history. We gather information on the age at which children started school, their annual school attendance, the grade they attended, and whether the school was private or public. This approach creates variability in exposure, allowing us to compare children of the same age with different educational histories. Finally, to address potential selection bias regarding the type of school attended, we use a Heckman Selection model. This methodology accounts for the parental choice of school type. Our results show that the MDMS benefits students regardless of the type of school attended, highlighting the need for nutritional support across the entire student population.

3. Data and Mid-Day Meal Scheme Exposure

We use data from the Indian Young Lives survey, which primarily aims to investigate children's development from childhood to adolescence and examine how various dimensions of poverty at the household and individual levels impact this development. This dataset is particularly suitable for our research due to its rich information on household and child characteristics and its unique structure, which includes two cohorts of children born in different years in the Indian State of Andhra Pradesh. The young cohort consists of 2,000 children born in 2000/2001, while the old cohort comprises 1,000 children born in 1994/1995. Each cohort was interviewed over five rounds (2002, 2007, 2009/2010, 2013/2014 and 2016/2017).[2]

Spanning 15 years from 2002 to 2017, the survey is ideal for studying the short- and medium-run impact of the Mid-Day Meal Scheme on children's health and cognitive outcomes. The MDMS timeline in Andhra Pradesh is crucial for the analysis (Figure 1). Following a November 2001 Indian Supreme Court order, the scheme was introduced nationally to provide cooked meals in all public and public-aided primary schools (grades I to V), with Andhra Pradesh implementing it in January 2003. The scheme was extended from grade VI to grade VIII (upper-primary schools) in 2007, with Andhra Pradesh following suit in October 2008 and further extending the benefit to grades IX and X (high schools). This phased implementation within the survey period allows for examining how varying exposure levels to the MDMS affect children's development outcomes.

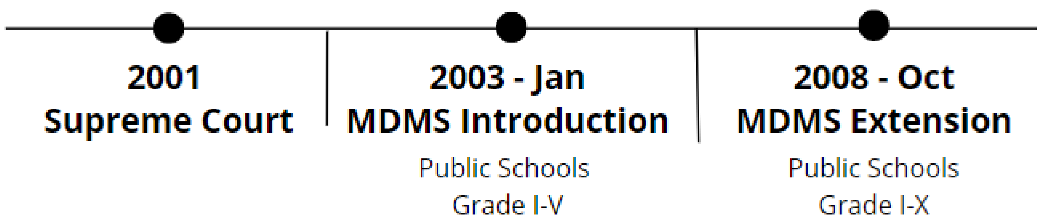
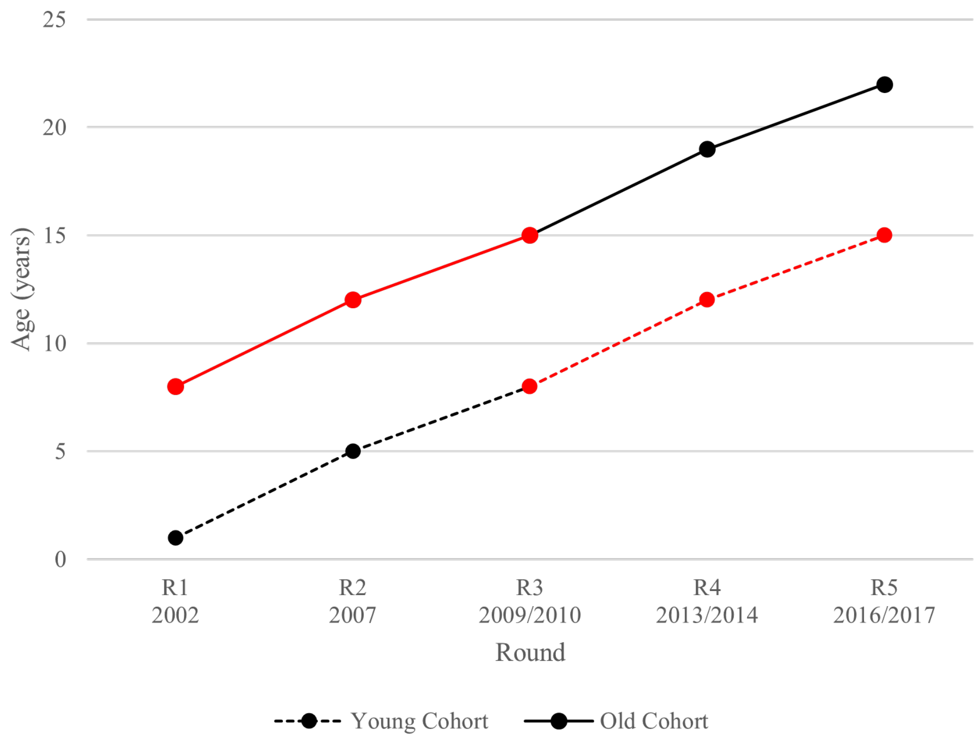


Figure 1: Mid-Day Meal Scheme in Andhra Pradesh

The dataset structure, encompassing two cohorts of children with an average age

[2]The survey maintained a low attrition rate, with only 3.7% for the younger cohort and 8.1% for the older cohort from the first to the last interview round (Young Lives, 2017)

difference of 7 years, interviewed in five rounds from 2002 to 2017, along with the phased implementation of the Mid-Day Meal Scheme in Andhra Pradesh, introduces variability in the exposure to the policy for children at similar ages. This heterogeneity allows us to investigate the impact of the monthly cumulative exposure to the Mid-Day Meal Scheme on the health and cognitive outcomes of children attending primary, upper-primary and high schools. The sample for the analyses includes all children enrolled in a public or private school between the ages of 7 and 16 years (in the final sample from 86 to 190 months), regardless of the cohort they belong to. For each cohort, we then selected the three interview rounds in which children fall in the specified age interval. The rounds considered are R1, R2 and R3 for the old cohort and R3, R4 and R5 for the young cohort (Figure 2).



In red are the selected rounds.
Own elaboration from the Indian Young Lives Survey.

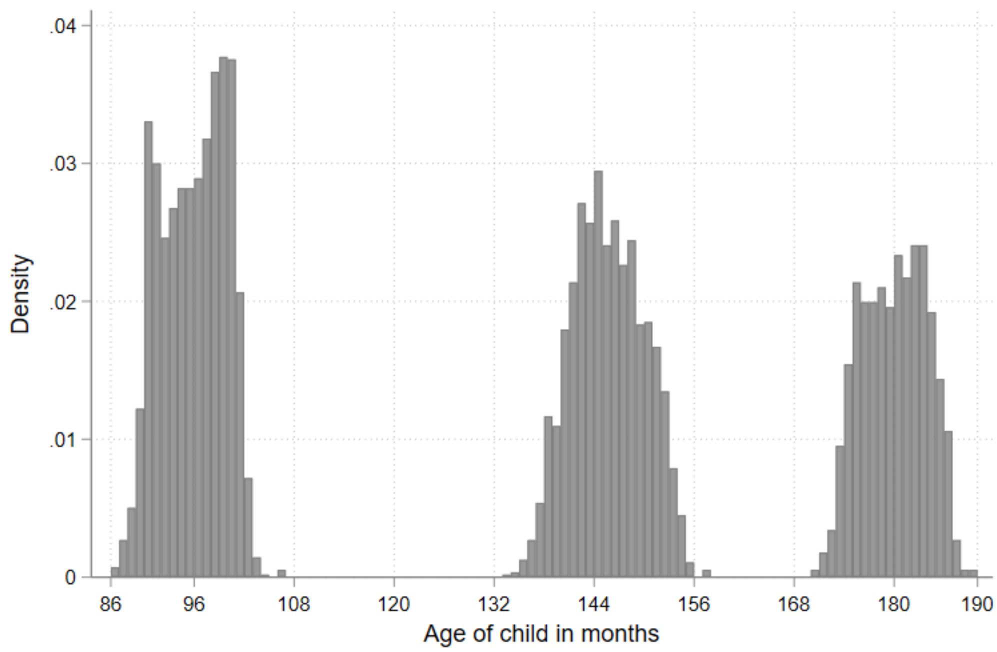
Figure 2: Sample definition

The selection of these specific rounds ensures that children from different cohorts have always been interviewed at a similar age but in different periods of time, a variation that is a key characteristic we utilize in defining our main variable of interest.[3] As illustrated in Figure 3, in the first interview round (R1 for the old cohort and R3 for the young cohort) children had an average age of 8 years (96

[3]Specifically, children of the same age and attending the same grade might experience different levels of exposure to the program

months), in the second round (R2 for the old cohort and R4 for the young cohort) their average age was 12 years (144 months) and in the third one it was 15 years (180 months) (R3 and R5).

From the sample of children attending public or private schools in the previously considered interview rounds, we select only those who consistently reported attending either a public or private school across all interview rounds. While this selection reduces the variability in the measure of cumulative exposure to the Mid-Day Meal Scheme, it offers the advantage of focusing exclusively on students committed to their educational career at a specific type of school. The students selected in the final sample are those from whom we expect both the largest between-group differences in health and cognitive outcomes and, for those attending public schools, the most significant potential impact of the policy. The total number of observations in the final sample varies depending on the outcome variable considered in the analysis. For the largest sample, we have information on 5,567 individuals ranging from 86 to 190 months of age (more than 7 and less than 16 years), of which 3,563 (64% of the total sample) attended a public school and 2,004 a private school.



Age of children in the health sample.
Own elaboration from the Indian Young Lives Survey.

Figure 3: Sample definition

Our main variable of interest, the child's cumulative monthly exposure to the MDMS, is calculated for each observation using retrospective information on the individual educational history. The survey collects data on the grade and type of school each child has attended since entering the formal schooling system, allowing us to define their complete educational history.

By combining the individual educational history with the design of the Mid-Day Meal Scheme, we define the cumulative exposure to the Mid-Day Meal Scheme for a child i at the time of interview t as the total number of months they were enrolled in a public school during the implementation of the Mid-Day Meal Scheme. The variability in monthly cumulative exposure arises from the longitudinal nature of the dataset, differences across birth cohorts, and variability within each interview round (Figure 4).

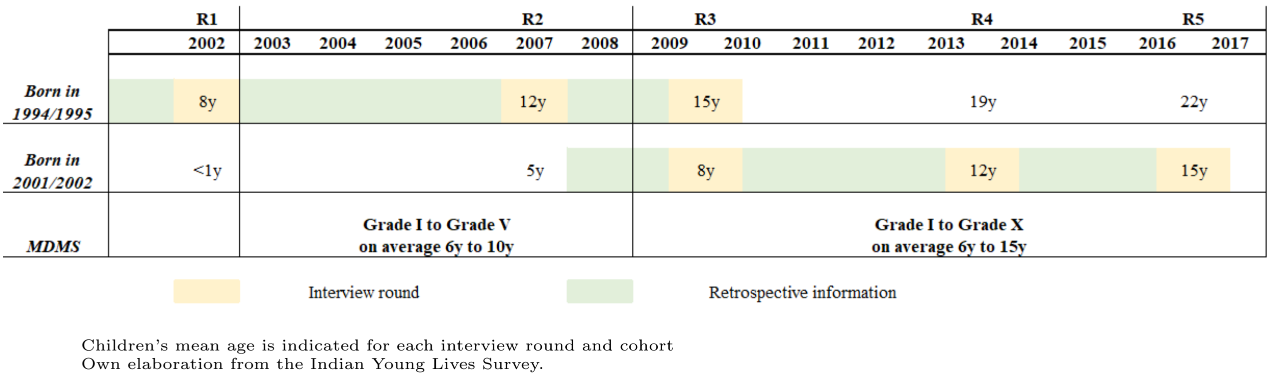
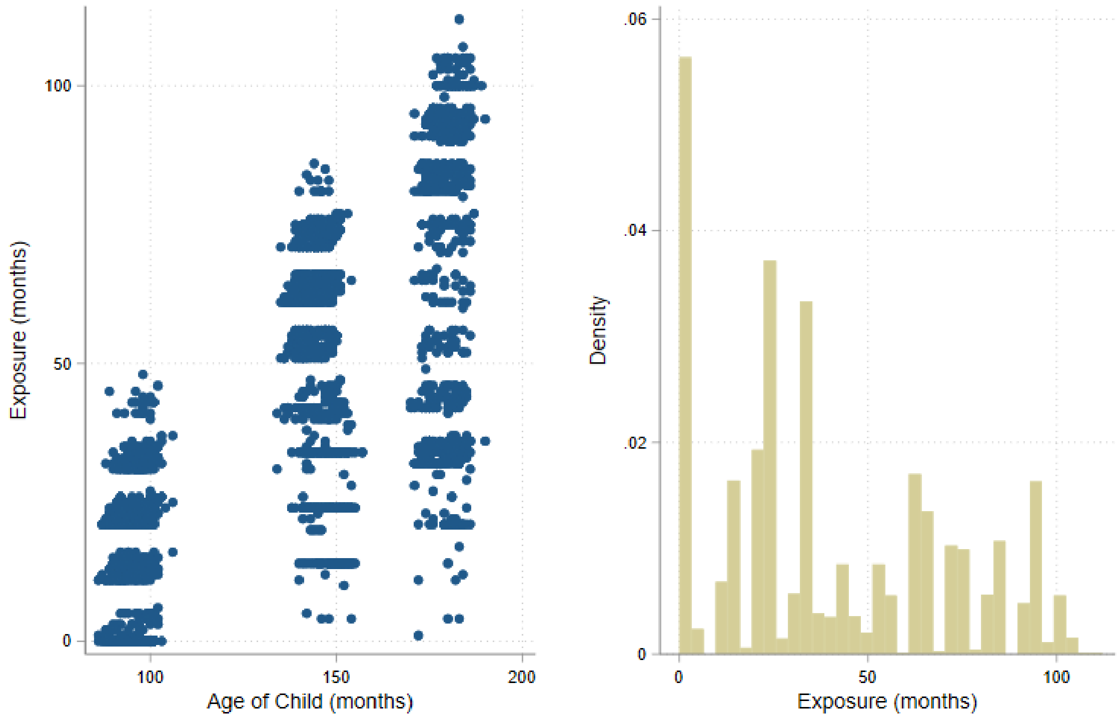


Figure 4: Young Lives Dataset and Mid-Day Meal Scheme

The different timing of the interviews, combined with the characteristics of the Mid-Day Meal Scheme, introduces variability in the cumulative exposure to the Mid-Day Meal Scheme. For example, consider two 12-year-old children from different cohorts, both enrolled in public schools and attending grade VI. If they started grade I at age 6, the first child from the old cohort would be interviewed in R2 (2007) and the second from the young cohort in R4 (2013/2014). The first child's cumulative exposure to the Mid-Day Meal Scheme would include all months from the initial introduction of the MDMS in January 2003 to the last month in grade V, starting primary school before the MDMS began.[4] The second child's exposure to the MDMS would be from the start of grade I in 2008/2009 (after the policy was extended to grade I to grade X) up to the interview month. To calculate the number of months of exposure, we consistently consider the school year starting in July and ending in April.

A potential concern for the construction of the exposure variable is the possible high correlation with the age in months of children enrolled in public schools. In Figure 5, we address this concern. The left panel shows a scatterplot illustrating

[4]The child entered primary school at age 6 in 2001/2002, before the policy's introduction, and was targeted by the Scheme up to grade V (the extension to grade X became operational only in 2008)



Exposure to the Scheme for children attending public schools in the health sample.
On the left: scatterplot of the exposure to MDMS on the age in months of children. On the right: histogram of the months of exposure to MDMS in the sample.
Own elaboration from the Indian Young Lives Survey.

Figure 5: Exposure to Mid-Day Meal Scheme

the lack of association between the cumulative number of months of exposure to the policy and the age in months of children attending public schools in the sample; children of the same age might exhibit different levels of exposure. The histogram in the right panel depicts the distribution of the number of months of exposure to the policy. The spike in density at 0 is due to observations from the 2002 interview round (R1), conducted before the introduction of the MDMS in 2003.

Our analysis explores the effects of cumulative exposure to the MDMS on two critical dimensions of child development: health and cognitive outcomes. We examine four outcomes: weight (in kilograms) and height (in centimetres) for health, and the scores of the Peabody-Picture Vocabulary Test (PPVT) and Math Test for cognition. Due to data limitations, the two cognitive tests were not performed in the first interview round, reducing our final sample for cognitive outcomes from 5,567 to 4,826 observations. Table 1 outlines the sizes and composition of the two samples based on children's gender and type of school attended. Notably, we observe gender-related inequalities in the frequency of children attending a public school, with females more likely to attend public schools, likely influenced by households' gender norms and preferences.

Table 1: Sample definition

	Health:			*Cognitive:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Public	3,563	1,665	1,898	2,934	1,361	1,573
Private	2,004	1,199	805	1,892	1,145	747
Conditional on gender						
Public	64.00%	58.13%	70.22%	60.80%	54.31%	67.80%
Private	36.00%	41.87%	29.78%	39.20%	45.69%	32.20%
Observations	5,567	2,864	2,703	4,826	2,506	2,320

When considering cognitive outcomes, the optimal approach, as outlined by Cunha and Heckman (2008), would be to anchor the scores obtained by each child to a variable (such as earnings) in adulthood; unfortunately, this is not feasible as we do not observe children after they exit schools. Given that test scores are measured on ordinal scales and lack a natural metric, any monotonic transformation, while not entirely satisfactory, serves as a valid alternative. For each interview round, we constructed the percentile ranking for each of the four dependent variables. This transformation is employed due to the challenge of directly comparing scores from different rounds, given changes in the number of items and questions. However, comparing rank positions remains feasible due to the characteristics of the two tests (Item Response Theory) and to a set of common items preserved in all interview rounds (Leon, 2020; Das and Zajonc, 2010). To be consistent throughout the research, we extend the use of percentile rankings, computed at the cohort-interview round level for health outcomes as well. In our analysis, the percentile ranking assigns a value between 100 and 0 to each observation within the same cohort and interview round. This process establishes rankings for children interviewed at the same time and of a similar age. The rank position for each specific outcome is determined by the individual value relative to all other values in the subsample. The percentile ranking defines the percentage of observations that fall at or below a specific value. For example, a child obtaining the highest score in the PPVT in a particular cohort interview round would be assigned a value of 100; the higher the percentile ranking the better the health or cognitive condition. As a robustness analysis, we also examine standardized outcome variables at the cohort-interview round level, with results consistent with those obtained using the percentile ranking strategy [5]..

We consider a rich set of covariates in every model specification. Table 2 presents

[5]Results using standardized outcome variables can be found in the Appendix, Tables A.5-A.8

Table 2: Descriptive statistics by type of school

	Private	Public	Difference		Private	Public	Difference
Female	0.402	0.533	-0.131***	Backward Caste	0.459	0.473	-0.014
	(0.011)	(0.008)	(0.014)		(0.011)	(0.008)	(0.014)
Rural	0.407	0.916	-0.509***	Hindu	0.821	0.909	-0.088***
	(0.011)	(0.005)	(0.010)		(0.009)	(0.005)	(0.009)
Natural Event	0.087	0.219	-0.132***	Telegu	0.822	0.826	-0.004
	(0.006)	(0.007)	(0.010)		(0.009)	(0.006)	(0.011)
Housing Quality	2.761	2.257	0.504***	Education Father	9.590	3.828	5.762***
(Quartile)	(0.024)	(0.018)	(0.030)		(0.107)	(0.074)	(0.127)
Ownhouse	0.700	0.914	-0.214***	Education Mother	7.083	2.098	4.985***
	(0.010)	(0.005)	(0.010)		(0.110)	(0.055)	(0.111)
Tv	0.892	0.484	0.409***	Household Size	5.102	5.207	-0.106*
	(0.007)	(0.008)	(0.012)		(0.045)	(0.033)	(0.056)
Bike	0.466	0.324	0.141***	Eldest child	0.591	0.417	0.174***
	(0,011)	(0.008)	(0.013)		(0.011)	(0.008)	(0.013)
Fan	0.958	0.711	0.247***	Rayalaseema	0.276	0.275	0.002
	(0.005)	(0.008)	(0.010)		(0.010)	(0.007)	(0.012)
Age Child	135.907	134.419	1.488	Telangana	0.442	0.312	0.130***
(months)	(0.784)	(0.580)	(0.972)		(0.011)	(0.008)	(0.013)
Age Child	19700.97	19267.67	433.296	Coastal Andhra	0.282	0.413	-0.131***
(square)	(213.109)	(157.075)	(263.457)		(0.010)	(0.008)	(0.013)
N. Obs	2,004	3,563			2,004	3,563	

List of covariates, group differences between children enrolled in private and public schools. Health sample.

individual and household characteristics by type of school for the health sample (with results valid for the cognitive sample as well). As expected, factors such as being a female, residing in a rural area or experiencing relative poverty increase the probability of a child being enrolled in a public school. Conversely, being the oldest child in the family or having parents with relatively higher education is associated with an increased likelihood of attending a private school. Additionally, wealth indicators, such as asset ownership and housing quality, confirm evidence found in the literature of wealthier households being those in which children are more frequently enrolled in private schools.

Table 3: Outcome variables by type of school

	Health Sample:				*Cognitive Sample*		
	Private	**Public**	**Difference**		**Private**	**Public**	**Difference**
Perc. Weight	60.325	44.322	16.003***	Perc. PPVT	57.717	43.356	14.361***
	(0.635)	(0.460)	(0.778)		(0.649)	(0.508)	(0.819)
Perc. Height	59.514	45.015	14.499***	Perc. Math	58.124	40.321	17.803***
	(0.632)	(0.467)	(0.783)		(0.631)	(0.500)	(0.802)
N. Obs	2,004	3,563			1,892	2,934	

Outcome variables, group differences between children enrolled in private and public schools.

Table 3 illustrates the mean values for our set of outcome variables for children attending different types of schools. As expected, children attending the private schooling system display systematically better outcomes in the percentile ranking of all four outcomes of interest, particularly with respect to Weight and Math scores.

4. Empirical Strategy

The primary goal of the Mid-Day Meal Scheme, is to support students' nutritional intake, potentially influencing their health and cognitive outcomes. By specifically targeting governmental schools, the policy enables us to examine not only whether the MDMS has improved the cognitive and health conditions of public school students, but also to measure these improvements relative to the inequalities existing between children attending public and private schools. To identify the magnitude of these inequalities in our outcome variables, we implement an Oaxaca-Blinder Decomposition strategy (Blinder, 1973; Oaxaca, 1973). This method decomposes the observed gap in outcome variables (R) into components explained by group differences in characteristics (Q) and an unexplained component representing group-related discrimination (U) (Jann, 2008).

$$R = E(Y_{pri}) - E(Y_{pub}) \tag{1}$$

Rearranging:

$$R = E(X_{pri})'\beta_{priv} - E(X_{pub})'\beta_{pub} \tag{2}$$

$$R = \underbrace{[E(X_{priv}) - E(X_{pub})]'\beta_{priv}}_{\text{Q = Explained}} + \underbrace{E(X_{pub})'(\beta_{priv} - \beta_{pub})}_{\text{U = Unexplained}}$$

We define the "Unadjusted Difference" as the raw difference in the values between the two groups (private and public schooling children) and the "Adjusted Difference" as the difference that is left unexplained after controlling for covariates. A positive Adjusted Difference indicates a higher return associated with attending private schools in terms of health and cognitive outcomes. Our analysis aims to determine the number of additional months of MDMS exposure required for a treated child to close this difference.

To assess the impact of the Mid-Day Meal Scheme on children's health and cognitive outcomes, we regress the percentile rankings of our dependent variables on the cumulative MDMS exposure and covariates, including year and region fixed effects. Equation (3) describes the regression equation. Y_{itr} denotes the percentile ranking of the dependent variable, $Exposure_{itr}$ quantifies the monthly cumulative exposure to MDMS for a child i interviewed at time t in region r, X_{itr} encompasses the set of covariates, τ_t and θ_r represent year and region fixed effects, and the error term is denoted by u_{itr}. Standard errors in this specification are clustered at time, gender and district level, with districts being smaller geographical units than regions.

$$Y_{itr} = \alpha + \gamma Exposure_{itr} + X'_{itr}\beta + \tau_t + \theta_r + u_{itr} \tag{3}$$

This specification is estimated by pooled OLS under the assumptions of strict exogeneity between covariates, and no correlation, at any period of time, between covariates and unobserved individual component c_i. To enhance the robustness of the estimates, a comprehensive set of covariates related to individual and family characteristics is included, along with year and region fixed effects. This approach controls for variations due to unobserved time-specific and regional characteristics. Additionally, the child's age in months is included as a covariate to account for the impact of child development at a highly granular level and to act as a cohort fixed effect. [6] The coefficient γ quantifies the average effect of an additional month of MDMS on the selected dependent variable. This helps to quantify how many additional months of exposure are needed for a public school child to close the adjusted outcome gap between different school types. With the aim of exploring potential gender inequalities in the impact of the MDMS on child development, we perform the analysis both on the entire sample of public schooling children and on the subsamples of male and female public schooling students. However, it is important to note that the dataset lacks information on whether children were effectively treated by the Mid-Day Meal Scheme. Therefore, our measure of exposure is based solely on the characteristics of the MDMS and the structure of our sample, meaning the results should be interpreted as an intention-to-treat (ITT) effect.

This analysis focuses specifically on children attending government schools, excluding those in private schools. Consequently, the results specifically reflect the impact of the Mid-Day Meal Scheme on the health and cognitive outcomes of children in public schools. The sample selection limits the generalizability of the results to the entire schooling population. It assumes that the decision made by parents to enrol a child in a specific type of school is exogenous to the outcome of interest. This assumption rules out the influence of unobserved factors that could affect both school choice and child outcomes. For instance, in the presence of limited resources, parents might decide to enrol children with better skills and better health in private schools in order to maximize educational returns (Kingdon, 2020; James and Woodhead, 2014). Additionally, budget constraints and parents' attitudes with respect to gender might lead to higher investments in health and education for male children (Sahoo, 2017). To address this concern, a Heckman Selection model is employed to account for the potential selection bias in school choice.

[6] The only interview round where both cohorts were surveyed simultaneously was in 2009/2010, with the old cohort averaging 15 years old and the young cohort 8. In this round, age in months determines the cohort, while in other rounds, time fixed effects control for cohort differences.

4.1 Heckman Model

The Heckman Selection Model is implemented in two-steps. First, we model the selection equation, using a probit specification to estimate the probability of a child being enrolled in a public school, incorporating an exclusion restriction to address endogeneity. In the second stage, the outcome equation, we estimate the impact of the MDMS on the outcome variables for the selected sample of public school children, correcting for the selection bias by including the Inverse Mills Ratio from the first stage. A bootstrap method is applied to obtain robust standard errors.

Equation (4) describes the first stage, where a probit regression models the probability for a child to attend a public school:

$$Pr(Public_{itr} = 1) = \alpha + X'_{itr}\delta + \phi Z_{id,t-5} + \tau_t + \theta_r + u_{itr} \tag{4}$$

The dependent variable $Public_{itr}$ is regressed on the set of covariates X_{itr}, on the year and region fixed effects τ_t, and θ_r and on an exclusion restriction $Z_{id,t-5}$. The exclusion restriction provides a source of exogenous variation in the selection process, helping to address the endogeneity issue. This restriction should influence the likelihood of attending a public school without directly affecting the health and cognitive outcomes in the second stage. The exclusion restriction used is a pre-determined measure from administrative sources (Statistical Abstract of Andhra Pradesh) that reflects the extent of public school provision at the local level. [7] For example, for a male child in West Godavari district, attending in 2002 a public or private primary school, the exclusion restriction would measure the percentage of male children enrolled in primary public schools in 1997 relative to all male children in primary school in that district. The variable captures the heterogeneity in public school availability and district-level attitudes towards alternative educational systems, affecting school enrollment likelihood at time t without directly impacting individual health and cognitive outcomes. The exposure to the Mid-Day Meal Scheme is excluded from the first stage because it depends on the parental decision to enrol and keep the child in a public school. In the second stage of the model, we use the selected sample of children attending public schools to measure the impact of the MDMS on the health and cognitive outcomes of the entire schooling population.

$$Y_{itr} = \alpha + \gamma Exposure_{itr} + X'_{itr}\beta + \omega\lambda_{itr} + \tau_t + \theta_r + \varepsilon_{itr} \tag{5}$$

This stage is specified as a linear regression (5), akin to the one utilized in the OLS

[7] For a child i observed at time t, this variable is defined as the proportion of children in public schools relative to the total number of children enrolled at school at time *t-5*, by gender, district d and schooling level.

model, with the Inverse Mills Ratio λ_{itr} included on the right-hand side of the equation. The Inverse Mills Ratio, estimated from the first stage, corrects the selection bias in the sample. A statistically significant coefficient for this ratio indicates the presence of selection in the types of schools in the sample. The coefficient of our main variable of interest γ, estimated through a two-stage Heckman Selection model, will then describe the policy's impact on the outcome variable Y_{itr} regardless of the type of school attended by children, accounting for the potential selection bias. The Heckman Selection model is computed following a two-step procedure to relax the assumption of joint normality of the error terms in the two stages, u_{itr} and ε_{itr} where η is an independent error:

$$\begin{aligned} u_{itr} &\sim N(0,1) \\ \varepsilon_{itr} &= \sigma u_{itr} + \eta \end{aligned} \tag{6}$$

The standard errors obtained through this two-step procedure are typically larger than those derived from maximum likelihood (ML) estimation. To account for this, we retrieve robust standard errors by employing a bootstrap estimation procedure, clustering at gender, district and time levels.

5 Results

5.1 Oaxaca-Blinder Decomposition and OLS estimates

Table 4 and Table 5 present the results of the Oaxaca-Blinder decomposition for the health and cognitive outcomes in the sample. The Unadjusted Difference captures the raw group difference in the mean outcome variables between children enrolled in private and public schools. A positive value indicates that, on average, children attending private schools have higher positions in the percentile rankings for weight, height and test scores, highlighting disparities in the health and cognitive conditions between the two groups. The Adjusted Difference is defined as the difference that is left unexplained in the model after controlling for a set of covariates, including individual characteristics like the child's age in months, household wealth indicators and parental education. Across all specifications, the Adjusted Difference remains positive and statistically significant, though its magnitude is reduced. This indicates that, even after controlling for individual and parental characteristics, significant disparities between the two groups persist, largely attributable to group affiliation.

Notably, the largest Adjusted Differences are observed in the female samples for all four outcomes. Female children in public schools exhibit greater disparities compared to their male counterparts, pointing to gender inequalities in health and

Table 4: Oaxaca-Blinder Decomposition, Health Outcomes

	Perc. Weight:			*Perc. Height:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Unadjusted Difference	16.003***	15.472***	17.294***	14.499***	14.017***	13.920***
	(1.038)	(1.377)	(1.348)	(1.014)	(1.500)	(1.539)
Adjusted Difference	7.784***	7.181***	8.738***	5.884***	6.151***	6.316***
	(1.114)	(1.766)	(1.670)	(1.210)	(1.648)	(1.539)
Region & Year FE	✓	✓	✓	✓	✓	✓
Child controls	✓	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓	✓
N. Obs	5,567	2,864	2,703	5,567	2,864	2,703

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

cognitive outcomes linked to educational choices. Overall, the Adjusted Differences account for approximately 36% to 49% of the Unadjusted Differences, leaving a substantial portion of inequalities unexplained. On average, children attending private schools are ranked 7.7 percentiles higher in weight and 5.9 percentiles higher in height than students in public schools. For cognitive outcomes, the difference ranges from around 5.3 percentiles for the PPVT to around 8.7 for the Math test. We anticipate that the Mid-Day Meal Scheme has the potential to mitigate these inequalities through mechanisms such as improving daily nutrition, reduced illnesses and school hunger, better concentration and increased time spent at school.

Table 5: Oaxaca-Blinder Decomposition, Cognitive Outcomes

	Perc. PPVT:			*Perc. Math:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Unadjusted Difference	14.361***	11.800***	16.638***	17.803***	16.143***	19.505***
	(1.447)	(1.708)	(2.084)	(1.364)	(1.755)	(1.890)
Adjusted Difference	5.285***	4.574***	6.307***	8.725***	8.466***	9.163***
	(1.142)	(1.347)	(1.465)	(1.425)	(1.828)	(2.083)
Region & Year FE	✓	✓	✓	✓	✓	✓
Child controls	✓	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓	✓
N. Obs	4,826	2,506	2,320	4,826	2,506	2,320

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

To further understand the potential of the Mid-Day Meal Scheme (MDMS) in addressing these inequalities, we turn to the results of the OLS specification, as presented in Tables 6 and 7. These results indicate the direct impact of MDMS on the health and cognitive outcomes of children attending public schools.

Table 6 shows that an additional month of exposure to the Mid-Day Meal Scheme has, on average, a positive statistically significant impact on both weight and height percentiles. Given the average exposure to the MDMS in the health sample, equal to 39.33 months (38.87 for males and 39.73 for females), we can calculate the average impact of exposure to the policy for public school students. This translates into an increase of 7.3 percentiles for weight (7.7 for males and 7.4 for females) and 11.6 percentiles for height (9.1 for males and 13.5 for females). Notably, while the impact on weight is similar between males and females, the effect on height is more pronounced for females with the coefficient almost 50% larger than males, suggesting a potential gender-specific impact of the scheme on height.

In Appendix Table A.1, we present the full set of results. It is important to note that the findings for other covariates align with expectations. Residing in rural areas has a negative impact on children's health outcomes, particularly for females, while coming from wealthier families is associated with better health. The coefficient for a child's age in months is positive and statistically significant, reflecting the expected influence of growth on weight and height.

Table 6: OLS, Health Outcomes

	Perc. Weight:			*Perc. Height:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Exposure (months)	0.186***	0.199**	0.185**	0.294**	0.233**	0.339***
	(0.061)	(0.082)	(0.017)	(0.079)	(0.092)	(0.105)
Region & Year FE	✓	✓	✓	✓	✓	✓
Child controls	✓	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓	✓
N. Obs	3,563	1,665	1,898	3,563	1,665	1,898

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

Similarly, Table 7 reveals a positive and statistically significant effect of the Mid-Day Meal Scheme on cognitive outcomes, as measured by the percentile rankings of the PPVT and Math test.[8] With an average exposure of 47.77 months, the

[8]As mentioned in the sample definition, when analyzing cognitive outcomes, we reduce the total number of observations due to the absence of these two particular tests in the first round of the survey (year 2002). Unfortunately, this exclusion results in the removal of the only round in the dataset where, by design, children attending public schools had no exposure to the MDMS (as the

policy results in a 10 percentile increase in PPVT (10.9 for males and 9 for females) and 21 percentile increase in Math scores (23 for males and 20 for females). The consistency in these effects across genders suggests that the policy does not favour one specific gender over the other in cognitive outcomes. The full set of results is shown in Table A.2 in the Appendix; also in this case, we observe covariates to have an impact on cognitive outcomes aligning with expectations. Children from wealthier families display better results, and parental education plays a crucial role, particularly mother's education for daughters.

Table 7: OLS, Cognitive Outcomes

	Perc. PPVT:			*Perc. Math:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Exposure (months)	0.209***	0.229**	0.188***	0.449***	0.482***	0.418***
	(0.054)	(0.101)	(0.065)	(0.066)	(0.106)	(0.082)
Region & Year FE	✓	✓	✓	✓	✓	✓
Child controls	✓	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓	✓
N. Obs	2,934	1,361	1,573	2,934	1,361	1,573

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

We contextualize the OLS results in relation to the observed inequality derived from the Oaxaca-Blinder decomposition. Indeed, the OLS findings underscore the policy's potential to reduce, though not completely eliminate, the disparities identified in the decomposition analysis. For instance, to close the weight gap observed in the Oaxaca-Blinder decomposition, an additional 42 months of exposure to the MDMS would be required for the entire sample, with specific needs of 36 months for males and 47 months for females [9]. The larger requirement for females, despite similar impacts of the policy, reflects the greater baseline disparities identified in the decomposition analysis.

For height, the required additional months are 20 for the entire sample, with females needing fewer months (19) than males (26), a discrepancy that can be at-

policy was introduced only in 2003). Nonetheless, the OLS model still yields statistically significant results regarding the impact of MDMS exposure on the cognitive outcomes of children attending public schools.

[9] To find the number of months required, consider the coefficient in the Oaxaca-Blinder Decomposition for the Adjusted Difference and divide it by the OLS coefficient for Exposure; e.g. for perc. weight

$$7.784/0.186 = 41.85$$

tributed to the larger height gains observed among females in the OLS results. In cognitive outcomes, closing the gap would require 25 additional months of exposure for PPVT and 19 months for the Math test, with variations across genders due to the different baseline disparities.

While these OLS results provide strong evidence of the MDMS's positive effects, it is essential to recognize potential limitations. A primary concern is endogeneity, which could bias the estimated effects. The inclusion of a comprehensive set of covariates, along with year and region fixed effects, helps mitigate this risk, lending credibility to the findings. However, the coefficient for monthly exposure may still partly capture natural growth in children, not solely the impact of the MDMS. To address this, age in months is controlled for in the model precisely to account for the individual growth of the child. This allows us to interpret the coefficient of exposure to the MDMS as the average impact of an additional month of exposure to the scheme on the outcomes.

In summary, the OLS results corroborate the positive influence of the MDMS on both health and cognitive outcomes in public school children with males, who generally benefit the most, except in the case of height percentile rankings. Height, a key indicator of long-term health capital, shows a larger impact for females, which is notable. While weight reflects short-term health, height measures cumulative health since birth. The greater effect on height for females suggests that despite possibly receiving fewer resources early in life, the scheme has helped bridge this gap, highlighting its role in improving the health of female children.

5.2 Heckman Model Estimates

While the OLS results offer valuable insights, another key limitation arises from potential selection bias, as the OLS analysis only captures children attending public schools. Children enrolled in public schools may be systematically different from those in private schools based on unobserved factors influencing both school choice and the outcomes of interest. To address this concern and ensure that the observed effects of the MDMS are not driven by selection into public school choice, we turn to the Heckman Selection model. This model accounts for selection bias by accounting for unobserved characteristics that influence both school enrollment and children's health and cognitive development, providing a more comprehensive view of the policy's impact across the school population.

The first stage of the Heckman model focuses on the exclusion restriction, which leverages district-level variation provision five years before the interview to predict the likelihood of a child being enrolled in a public school. Additionally, the exclusion restriction is also broken down by gender. This helps ensure the model considers

Table 8: Heckman Model, Health Outcomes

	Perc. Weight:			*Perc. Height:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Second Stage						
Exposure (months)	0.186***	0.199**	0.187**	0.294***	0.233**	0.342***
	(0.061)	(0.088)	(0.085)	(0.079)	(0.099)	(0.108)
Mills Ratio	−0.659	−0.698	3.105	0.352	1.329	4.279
	(4.170)	(5.406)	(5.060)	(3.797)	(5.191)	(4.287)
First Stage						
Exclusion Restriction	1.005***	1.209***	0.757***	1.005***	1.209***	0.757***
	(0.217)	(0.374)	(0.277)	(0.217)	(0.374)	(0.277)
Region & Year FE	✓	✓	✓	✓	✓	✓
Child controls	✓	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓	✓
N. Obs	5,567	2,864	2,703	5,567	2,864	2,703
Selected	3,563	1,665	1,898	3,563	1,665	1,898

*p<0.1; **p<0.05; ***p<0.01
Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

possible differences in school enrollment between genders, accounting for potential disparities in educational access and participation across genders. The exclusion restriction proves to be a strong and statistically significant predictor of school choice in all specifications, confirming its validity in addressing selection bias. Tables 8 and 9, which present the Heckman estimates for the health and cognitive sample, show that a 1 percentage point increase in the exclusion restriction raises the likelihood of public school enrollment by up to 1.2 percentage points for males and 0.75 percentage points for females. In the second stage, we assess the effect of cumulative exposure to the MDMS on the percentile rankings of health and cognitive outcomes, now controlling for the selection process. Crucially, the Inverse Mills Ratio, which accounts for selection bias, is not statistically significant in most cases, suggesting that selection into public or private schools does not drive the observed outcomes. This reinforces the validity of the OLS findings, as the Heckman model yields similar estimates of MDMS's impact on weight and height for both male and female students, as well as on cognitive outcomes like the PPVT and Math test.

These results indicate that the positive effects of the MDMS observed in the OLS analysis are not confined to public school children but extend across the broader schooling population. The consistency between the Heckman and OLS findings highlights the MDMS's capacity to improve health and cognitive outcomes irrespective

Table 9: Heckman Model, Cognitive Outcomes

	Perc. PPVT:			*Perc. Math:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Second Stage						
Exposure (months)	0.210***	0.229**	0.192***	0.448***	0.480***	0.420***
	(0.056)	(0.100)	(0.069)	(0.065)	(0.103)	(0.085)
Mills Ratio	3.719	1.201	7.784*	−1.572	−4.111	2.754
	(3.916)	(6.544)	(4.224)	(4.114)	(6.435)	(4.993)
First Stage						
Exclusion Restriction	1.009***	1.254***	0.784***	1.009***	1.254***	0.784***
	(0.239)	(0.444)	(0.288)	(0.239)	(0.444)	(0.288)
Region & Year FE	✓	✓	✓	✓	✓	✓
Child controls	✓	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓	✓
N. Obs	4,826	2,506	2,320	4,826	2,506	2,320
Selected	2,934	1,361	1,573	2,934	1,361	1,573

*p<0.1; **p<0.05; ***p<0.01
Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

of the type of school children attend [10] [11].

In sum, the Heckman Selection model confirms that the MDMS plays a critical role in enhancing children's development, addressing disparities not only between public and private school students but also within gender groups. The program's ability to improve both health and cognition across diverse schooling environments emphasizes the potential of school feeding programs to reduce inequalities in India as well as in other developing countries.

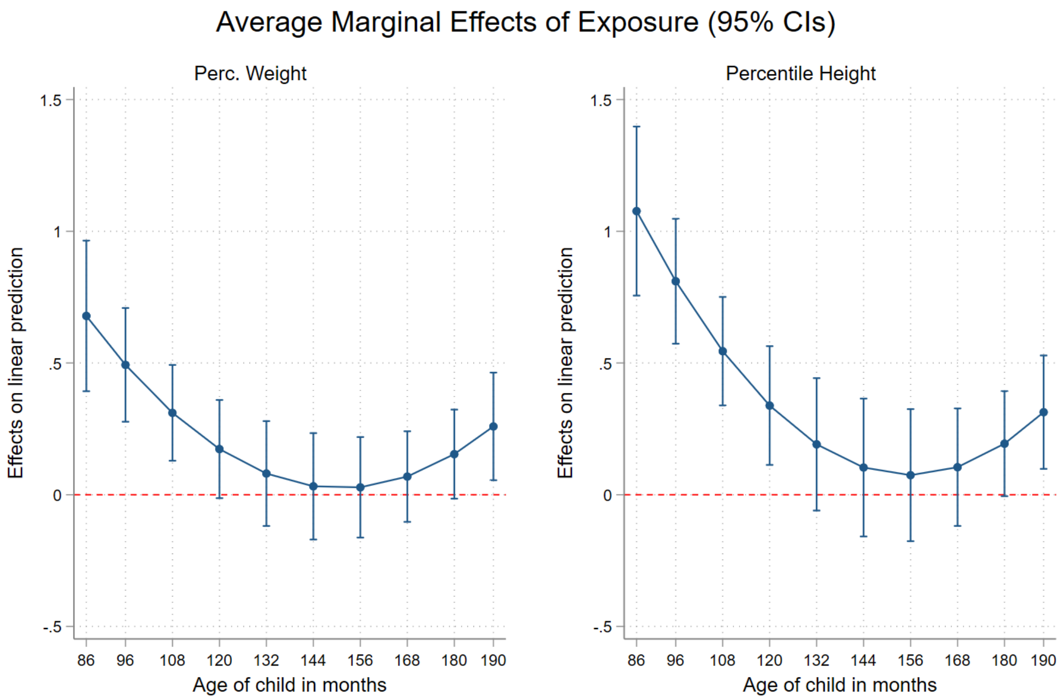
5.3 Age Heterogenity

All the specifications examined so far identify the average impact of the Mid-Day Meal Scheme on the health and cognitive outcomes of children, regardless of the age at which they receive support from the policy. However, children in our sample range are between 7 and nearly 16 years of age, and we may expect potential variability in the magnitude of the scheme's impact depending on their age at the

[10] Table A.3 and A.4 in the Appendix describe the results for the complete set of covariates used in the model.

[11] We find consistency between OLS estimates and Heckman ones also using standardized outcome variables; results can be found in the Appendix, Tables A.5 and A.6 for OLS and Tables A.7 and A.8 for Heckman model.

time of the interview. Children in the initial years of formal schooling might derive larger benefits from the program compared to those in higher grades. The literature provides evidence that School Feeding Programs and, in general, programs aimed at supporting children's development tend to produce larger improvements when children are in the early stages of their lives (Cunha and Heckman, 2008; Cascio and Staiger, 2012; Attanasio et al., 2020). To account for this potential heterogeneity, we incorporate an interaction term in the second stage of the Heckman Selection model by multiplying the monthly cumulative exposure to the Mid-Day Meal Scheme with the child's age in months and its squared term. These interactions allow us to identify the non-linear impact of an additional month of exposure to the MDMS and describe the marginal impact of the policy based on the children's age. Our examination spans the entire age range in the sample, from 86 months (7 years and 2 months) to 190 months (15 years and 10 months). However, due to limited observations at the extremes of this interval, we focus primarily on assessing the impact on children aged 8 to 15 years.

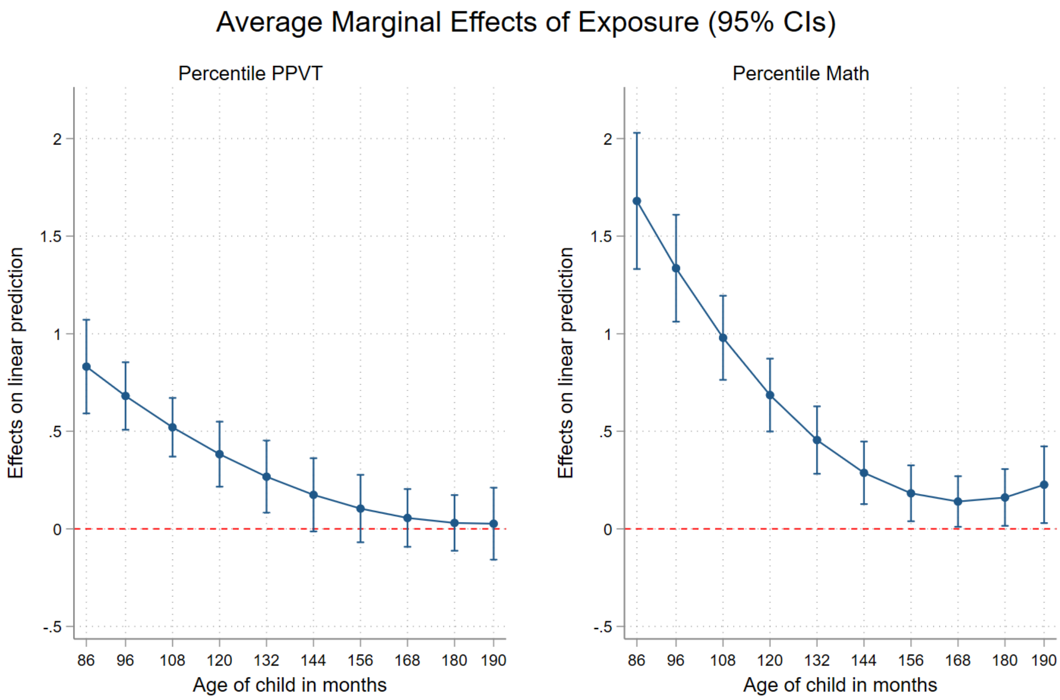


Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels.
Average treatment effect of exposure to Mid-Day Meal Scheme at different ages on health outcomes. Range from 86 (min) to 190 (max) months, any additional tick represents a year.

Figure 6: Age Heterogeneity, Health Outcomes

Figure 6 illustrates the variation in the average impact of an additional month of exposure to the Mid-Day Meal Scheme on the percentile rankings of weight and height across different age groups. The graphs reveal a U-shaped pattern, with the

most substantial effect observed among children entering the schooling system and diminishing as age increases. Notably, the coefficient loses statistical significance approaching zero impact for children older than 10 and younger than 16 years of age. Interestingly, the effect regains statistical significance for the few children in the sample who are the oldest, nearing 16 years of age.
Similarly, Figure 7 shows the average marginal effect of the exposure to the policy across various age groups in the cognitive sample. Here, too, the marginal impact diminishes with age, but the effect remains statistically significant for a longer period of growth, from about 7 to almost 12 years of age. Notably, for the math test, the effect remains positive and statistically significant at any age despite decreasing point estimates [12].



Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels.
Average treatment effect of exposure to Mid-Day Meal Scheme at different ages on cognitive outcomes. Range from 86 (min) to 190 (max) months, any additional tick represents a year.

Figure 7: Age Heterogeneity, Cognitive Outcomes

This heterogeneity analysis confirms that the youngest age groups, primarily children in primary school, benefit most from the Mid-Day Meal Scheme. Unfortunately, our dataset lacks information to assess whether a redistribution mechanism within the household, as suggested by Jacoby (2002), could limit the effectiveness of the transfer received by the child. However, the results suggest that if such a mechanism exists, it is unlikely to affect very young children. Additionally, we are unable

[12]Figure A.1 and A.2 in the Appendix reproduce the same analysis by gender

to investigate whether the absence of an effect for older children could be due to an insufficient amount of daily calories provided by the school meal program. This could become an issue if the calories provided by the school meal are not enough to meet the increasing needs of older children. A combination of the two effects is also possible. Over time, households may adjust the total daily food they provide during other meals in response to the food transfer received by the child at school. If the MDMS does not adequately address the growing calorie needs of children, and households fail to compensate for the shortfall, the policy's impact could become negligible. Notably, the effect of the policy on cognitive outcomes seems to persist for a longer period, potentially due to increased time spent at school or a reduction in days missed due to illness.

6. Conclusion

In our research, we examine the impact of the Indian Mid-Day Meal Scheme, one of the world's largest School Feeding Programs, on a set of outcomes describing the health and cognitive development of schoolchildren aged 7 to 16 years old living in the Indian State of Andhra Pradesh. Specifically, we analyse the impact of the policy with respect to the weight and height of children and their performance on two cognitive tests, the PPVT and the Math Test. The policy, discriminating between children enrolled in different types of schools, has the potential not just to enhance the development of students attending public schools but also to reduce inequalities that exist between children enrolled in the private and public sectors. Indeed, through an Oaxaca-Blinder Decomposition, we find that disparities in the two dimensions between children enrolled in different types of schools, private and public, persist even after accounting for a comprehensive set of individual and familial characteristics. Notably, these differences are most pronounced among female children. To analyse the extent to which the MDMS can reduce these inequalities, we leverage the design of the Indian Young Lives Survey and the phased implementation of the MDMS, targeting only children attending public schools at specific grades in specific years, to construct a variable describing the individual monthly cumulative exposure to the policy at each interview round, utilizing the complete educational history of each child. Initially, we perform an OLS analysis on the sample of children attending public school to measure the impact that an additional month of exposure to the policy has on the health and cognitive outcomes considered. The results reveal a positive and statistically significant impact of the MDMS on both health and cognitive outcomes, underscoring the program's significance in supporting the development of public school students and also allowing the calculation of the number of additional months of exposure that would be needed to close the observed gaps identified in the Oaxaca-Blinder Decomposition.

The interpretation of the OLS results, however, is limited to the population of students in public schools and cannot provide answers to the broader question of how the policy would affect the entire school population. The OLS results can only be generalized to the overall student population if the decision to attend a particular type of school is exogenous. This assumption excludes the existence of unobserved characteristics that could affect both the outcomes of interest and the school choice, which determines the exposure to the MDMS. To address this potential selection issue, we employ a two-step Heckman Selection model, which accounts for parental decisions in school choice. The results indicate that the impact of the MDMS on students in our sample would be positive and statistically significant, regardless of the type of school attended.

Finally, to investigate whether the impact of the policy varies with the age of the child, we conduct a heterogeneity exercise by interacting the monthly exposure to the MDMS with the child's age in months. The analysis confirms that the groups of children benefiting the most from the School Feeding Program are the youngest, particularly in terms of health outcomes.

Our analysis underscores the importance of School Feeding Programs, such as the Indian Mid-Day Meal, in supporting children's development and reducing early-life inequalities. In all the specifications considered, males seem to benefit slightly more with respect than females in most outcomes, except for height, where females show stronger gain, highlighting the crucial role the policy plays in supporting health capital accumulation, especially among girls. While our findings provide insights into the effects of the MDMS on students in Andhra Pradesh, they also offer valuable guidance for policymakers, emphasizing the diminishing impact of nutrition programs as children age and the crucial role these programs play in female health capital accumulation. In the Indian context, where the private sector is expanding to children coming from lower socioeconomic groups, extending the Mid-Day Meal Scheme to students attending private schools would be beneficial for the overall development of the entire schooling population.

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Appendix

Table A.1: OLS, Health Outcomes

	Perc. Weight:			*Perc. Height:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Exposure (months)	0.186***	0.199**	0.185**	0.294**	0.233**	0.339***
	(0.061)	(0.082)	(0.017)	(0.079)	(0.092)	(0.105)
Gender	1.111			−4.378**		
	(1.443)			(1.792)		
Rural	−6.455***	−5.747	−7.110**	−1.391	2.825	−5.390
	(2.424)	(4.042)	(2.961)	(2.568)	(3.090)	(3.386)
Housing Quality 2nd quartile	0.311	0.770	0.245	1.669	3.259**	−0.127
	(1.023)	(1.564)	(1.427)	(1.162)	(1.593)	(1.753)
Housing Quality 3rd quartile	0.592	1.665	−0.850	1.821	2.343	0.362
	(1.175)	(2.056)	(1.416)	(1.376)	(1.860)	(2.034)
Housing Quality 4th quartile	1.122	0.186	2.163	1.653	0.669	2.777*
	(1.336)	(1.885)	(1.750)	(1.593)	(2.731)	(1.475)
Ownhouse	−3.176*	−5.078**	−1.390	−5.755***	−9.004***	−2.259
	(1.805)	(2.521)	(2.597)	(1.837)	(1.750)	(2.812)
TV	3.260**	1.997	3.901*	4.335***	3.709**	4.891**
	(1.290)	(1.524)	(2.134)	(1.208)	(1.499)	(1.887)
Bike	1.983*	0.853	2.683*	2.628**	0.954	2.488*
	(1.032)	(1.178)	(1.411)	(1.042)	(1.431)	(1.246)
Fan	1.889	4.068**	0.001	1.788	3.677*	0.810
	(1.238)	(1.602)	(1.657)	(1.313)	(1.922)	(1.853)
Natural Event	−0.505	0.436	−1.366	0.010	0.432	−0.506
	(1.258)	(1.435)	(1.801)	(1.585)	(1.634)	(1.863)
Age Child (months)	1.668***	0.694	2.550***	1.924***	1.021	2.734***
	(0.601)	(0.883)	(0.720)	(0.598)	(0.951)	(0.698)
Age Child squared	−0.006***	−0.003	−0.009***	−0.007	−0.003	−0.010***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Backward Caste	−2.581**	−1.172	−3.963***	2.412*	2.119	2.428
	(1.017)	(1.397)	(1.403)	(1.370)	(1.737)	(2.053)
Hindu	4.748***	5.547***	4.799*	1.309	2.916	−0.135
	(1.541)	(1.891)	(2.577)	(1.833)	(1.778)	(3.010)
Telegu	−1.835*	0.576	−4.166**	−2.161	−1.396	−2.968*
	(1.089)	(1.193)	(1.629)	(1.357)	(1.989)	(1.515)
Education Father	0.120	−0.404***	0.522***	0.058	−0.326*	0.336**
	(0.130)	(0.150)	(0.147)	(0.129)	(0.190)	(0.131)
Education Mother	0.106	0.302	−0.038	0.273	0.297	0.182
	(0.142)	(0.230)	(0.187)	(0.167)	(0.236)	(0.235)
Household Size	−0.460*	−0.378	−0.547*	−0.316	−0.424	−0.167
	(0.234)	(0.342)	(0.283)	(0.230)	(0.354)	(0.279)
First Child	1.912	2.364	1.695	2.247**	2.433*	2.768**
	(1.285)	(1.765)	(1.796)	(0.948)	(1.350)	(1.316)
Region & Year FE	✓	✓	✓	✓	✓	✓
N. Obs	3,563	1,665	1,898	3,563	1,665	1,898
R-squared	0.058	0.078	0.098	0.060	0.106	0.120
F	13.33	23.40	50.22	15.33	44.13	86.59

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

Table A.2: OLS, Cognitive Outcomes

	Perc. PPVT:			*Perc. Math:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Exposure (months)	0.209***	0.229**	0.188***	0.449***	0.482***	0.418***
	(0.054)	(0.101)	(0.065)	(0.066)	(0.106)	(0.082)
Gender	−5.818***			−4.042***		
	(1.616)			(1.403)		
Rural	−5.830**	1.186	−11.068***	3.843**	7.187***	1.451
	(2.428)	(4.107)	(2.683)	(1.815)	(2.572)	(2.558)
Housing Quality 2nd quartile	−1.758	−0.334	−2.744	−0.411	0.093	−0.493
	(1.378)	(2.130)	(1.661)	(1.002)	(1.376)	(1.479)
Housing Quality 3rd quartile	−2.528	−4.139	−0.850	−0.268	1.628	−2.147
	(1.670)	(1.998)	(2.499)	(1.365)	(1.916)	(1.645)
Housing Quality 4th quartile	−3.503**	−4.165*	2.163	−0.919	0.830	−1.852
	(1.481)	(1.922)	(2.163)	(2.097)	(3.219)	(2.793)
Ownhouse	0.788	−3.972	3.566	2.374	−2.063	5.565***
	(1.759)	(2.755)	(2.391)	(1.652)	(2.407)	(2.001)
TV	3.356***	2.683*	3.733**	0.462	−0.683	1.086
	(1.056)	(1.569)	(1.562)	(0.991)	(1.446)	(1.340)
Bike	2.291*	2.130	2.303	0.375	−2.282	2.496
	(1.365)	(1.536)	(2.028)	(1.563)	(2.427)	(1.654)
Fan	3.885***	4.344**	3.216	6.912***	8.151***	5.918***
	(1.456)	(1.841)	(2.265)	(1.559)	(2.438)	(2.017)
Natural Event	−0.286	2.229	−2.205	0.473	2.754	−1.554
	(1.946)	(2.495)	(2.724)	(1.376)	(2.319)	(1.523)
Age Child (months)	0.435	−0.247	0.903	0.688	1.224*	0.117
	(0.484)	(0.632)	(0.658)	(0.495)	(0.658)	(0.649)
Age Child squared	−0.002	0.001	−0.004	−0.003	−0.005*	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Backward Caste	−3.346***	−3.871**	−3.361**	0.367	−0.024	0.349
	(1.168)	(1.907)	(1.359)	(1.447)	(1.962)	(1.572)
Hindu	2.070	5.276*	−0.603	6.344***	8.716***	3.881**
	(1.593)	(2.808)	(1.881)	(1.447)	(2.100)	(1.825)
Telegu	0.970	1.909	0.553	1.048	0.792	1.774
	(1.471)	(2.367)	(1.853)	(1.353)	(2.062)	(1.813)
Education Father	0.435***	0.498***	0.425**	0.443***	0.234*	0.583***
	(0.132)	(0.175)	(0.192)	(0.132)	(0.232)	(0.177)
Education Mother	0.825***	0.615**	0.848***	0.999***	0.884***	0.997***
	(0.158)	(0.234)	(0.212)	(0.198)	(0.319)	(0.267)
Household Size	−0.302	−0.629**	0.060	0.403	0.062	0.751**
	(0.205)	(0.294)	(0.297)	(0.247)	(0.281)	(0.327)
First Child	2.726***	3.264**	2.466*	3.105***	3.130	3.585***
	(0.998)	(1.341)	(1.409)	(0.993)	(1.995)	(0.831)
Region & Year FE	✓	✓	✓	✓	✓	✓
N. Obs	2,934	1,361	1,573	2,934	1,361	1,573
R-squared	0.132	0.143	0.135	0.160	0.164	0.184
F	29.86	63.41	98.41	25.04	80.75	349.09

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

Table A.3: Heckman Model, Health Outcomes

	Perc. Weight:			*Perc. Height:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Second Stage						
Exposure (months)	0.186***	0.199**	0.187**	0.294***	0.233**	0.342***
	(0.061)	(0.088)	(0.085)	(0.079)	(0.099)	(0.108)
Mills Ratio	−0.659	−0.698	3.105	0.352	1.329	4.279
	(4.170)	(5.406)	(5.060)	(3.797)	(5.191)	(4.287)
Gender	1.019			−4.330**		
	(1.704)			(2.076)		
Rural	−6.847*	−6.151	−5.166	−1.181	3.593	−2.713
	(3.944)	(5.480)	(5.250)	(3.739)	(4.353)	(5.214)
Housing Quality 2nd quartile	0.366	0.795	0.140	1.656	3.211*	−0.273
	(1.041)	(1.601)	(1.500)	(1.198)	(1.678)	(1.832)
Housing Quality 3rd quartile	0.666	1.763	−1.129	1.781	2.156	−0.022
	(1.257)	(2.203)	(1.576)	(1.490)	(2.120)	(2.202)
Housing Quality 4th quartile	1.251	0.332	1.599	1.585	0.390	2.000
	(1.680)	(2.404)	(2.146)	(1.904)	(3.386)	(1.866)
Ownhouse	−3.207*	−5.068**	−1.124	−5.739***	−9.023***	−1.892
	(1.817)	(2.523)	(2.754)	(1.860)	(1.892)	(2.989)
TV	3.365***	2.118	3.451*	4.279***	3.478*	4.271**
	(1.288)	(1.714)	(2.002)	(1.222)	(1.908)	(1.749)
Bike	1.981*	0.861	2.756*	2.630**	0.939	2.589**
	(1.063)	(1.203)	(1.561)	(1.056)	(1.459)	(1.308)
Fan	1.911	4.077**	−0.142	1.775	3.660*	0.614
	(1.270)	(1.634)	(1.649)	(1.330)	(1.962)	(1.958)
Natural Event	−0.529	0.409	−1.283	0.023	0.483	−0.392
	(1.261)	(1.550)	(1.826)	(1.510)	(1.690)	(1.899)
Age Child (months)	1.670***	0.683	2.582***	1.929***	1.041	2.777***
	(0.681)	(0.955)	(0.770)	(0.599)	(1.011)	(0.747)
Age Child squared	−0.006***	−0.003	−0.009***	−0.007***	−0.003	−0.011***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)
Backward Caste	−2.589**	−1.128	−3.717**	2.416*	2.035	2.767
	(1.022)	(1.491)	(1.596)	(1.402)	(1.850)	(2.119)
Hindu	4.762***	5.549***	4.684*	1.301	2.913	−0.294
	(1.577)	(1.990)	(2.610)	(1.813)	(1.817)	(3.109)
Telegu	−1.805	0.589	−4.340***	−2.177	−1.421	−3.235**
	(1.135)	(1.258)	(1.665)	(1.344)	(2.073)	(1.515)
Education Father	0.136	−0.381*	0.747**	0.050	−0.370	0.270*
	(0.174)	(0.216)	(0.194)	(0.174)	(0.253)	(0.158)
Education Mother	0.125	0.323	−0.123	0.263	0.257	0.065
	(0.171)	(0.314)	(0.211)	(0.197)	(0.309)	(0.258)
Household Size	−0.461*	−0.378	−0.540*	−0.315	−0.424	−0.157
	(0.239)	(0.362)	(0.299)	(0.237)	(0.369)	(0.308)
First Child	1.963	2.408	1.469	2.220**	2.350	2.457**
	(1.320)	(1.987)	(1.657)	(0.968)	(1.517)	(1.185)
Region & Year FE	✓	✓	✓	✓	✓	✓
First Stage						
Exclusion Restriction	1.005***	1.209***	0.757***	1.005***	1.209***	0.757***
	(0.217)	(0.374)	(0.277)	(0.217)	(0.374)	(0.277)
N. Obs	5,567	2,864	2,703	5,567	2,864	2,703
Selected	3,563	1,665	1,898	3,563	1,665	1,898

*p<0.1; **p<0.05; ***p<0.01
Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

Table A.4: Heckman Model, Cognitive Outcomes

	Perc. PPVT:			*Perc. Math:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Second Stage						
Exposure (months)	0.210***	0.229**	0.192***	0.448***	0.480***	0.420***
	(0.056)	(0.100)	(0.069)	(0.065)	(0.103)	(0.085)
Mills Ratio	3.719	1.201	7.784*	−1.572	−4.111	2.754
	(3.916)	(6.544)	(4.224)	(4.114)	(6.435)	(4.993)
Gender	−5.198**			−4.304**		
	(2.110)			(1.800)		
Rural	−3.619	1.860	−6.105	2.909	4.879	3.206
	(3.803)	(6.163)	(4.212)	(3.351)	(5.099)	(4.440)
Housing Quality 2nd quartile	−1.939	−0.407	−2.992*	−0.335	0.344	−0.581
	(1.411)	(2.372)	(1.783)	(1.038)	(1.530)	(1.518)
Housing Quality 3rd quartile	−2.995	−1.187	−4.847*	−0.071	2.328	−2.398
	(1.833)	(2.422)	(2.659)	(1.513)	(2.049)	(1.830)
Housing Quality 4th quartile	−4.393**	−2.535	−5.888**	−0.543	1.886	−2.462
	(1.956)	(2.757)	(2.616)	(2.403)	(4.022)	(3.069)
Ownhouse	1.043	−3.801	4.453*	2.266	−2.048	5.879***
	(1.853)	(2.758)	(2.526)	(1.780)	(2.573)	(2.200)
TV	2.783**	2.481	2.651	0.705	0.010	0.704
	(1.287)	(2.214)	(1.814)	(1.173)	(1.830)	(1.550)
Bike	2.285*	2.123	2.359	0.377	−2.259	2.516
	(1.337)	(1.652)	(2.004)	(1.540)	(2.451)	(1.529)
Fan	3.808***	4.344**	2.936	6.945***	8.150***	5.819***
	(1.468)	(1.984)	(2.318)	(1.580)	(2.402)	(2.142)
Natural Event	−0.225	2.257	−2.172	0.447	2.659	−1.542
	(1.969)	(2.570)	(2.828)	(1.370)	(2.361)	(1.538)
Age Child (months)	0.497	−0.233	1.044	0.662	1.174	0.167
	(0.526)	(0.721)	(0.743)	(0.524)	(0.735)	(0.750)
Age Child squared	−0.002	0.001	−0.004	−0.002	−0.004	−0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Backward Caste	−3.294***	−3.940*	−2.734**	0.345	0.214	0.571
	(1.113)	(2.100)	(1.375)	(1.196)	(2.329)	(1.574)
Hindu	1.942	5.247*	−0.883	6.399***	8.815***	3.782**
	(1.593)	(2.794)	(1.860)	(1.462)	(2.284)	(1.908)
Telegu	0.759	1.874	−0.023	1.137	0.908	1.570
	(1.445)	(2.343)	(1.908)	(1.319)	(2.082)	(1.710)
Education Father	0.342**	0.457	0.288	0.482***	0.376	0.535***
	(0.165)	(0.296)	(0.219)	(0.171)	(0.322)	(0.199)
Education Mother	0.706**	0.572*	0.628**	1.050***	1.029**	0.919***
	(0.208)	(0.306)	(0.268)	(0.253)	(0.436)	(0.318)
Household Size	−0.310	−0.633**	0.055	0.407	0.077	0.749**
	(0.221)	(0.323)	(0.316)	(0.252)	(0.338)	(0.357)
First Child	2.392**	3.166**	1.850	3.246***	3.463*	3.368***
	(1.145)	(1.587)	(1.636)	(1.035)	(2.096)	(0.897)
Region & Year FE	✓	✓	✓	✓	✓	✓
First Stage						
Exclusion Restriction	1.009***	1.254***	0.784***	1.009***	1.254***	0.784***
	(0.239)	(0.444)	(0.288)	(0.239)	(0.444)	(0.288)
N. Obs	4,826	2,506	2,320	4,826	2,506	2,320
Selected	2,934	1,361	1,573	2,934	1,361	1,573

*p<0.1; **p<0.05; ***p<0.01
Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

Table A.5: OLS, Health Outcomes - Standardised Scores

	Std. Weight:			*Std. Height:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Exposure (months)	0.050**	0.006**	0.005*	0.010***	0.008**	0.011***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.04)
Gender	0.026			−0.165***		
	(0.044)			(0.059)		
Rural	−0.251***	−0.234	−0.266**	−0.055	0.101	−0.199*
	(0.086)	(0.145)	(0.104)	(0.087)	(0.104)	(0.117)
Housing Quality 2nd quartile	0.015	0.036	0.012	0.057	0.110**	−0.001
	(0.032)	(0.053)	(0.042)	(0.039)	(0.054)	(0.058)
Housing Quality 3rd quartile	0.015	0.047	−0.023	0.053	0.069	0.006
	(0.038)	(0.063)	(0.049)	(0.046)	(0.061)	(0.067)
Housing Quality 4th quartile	0.044	0.020	0.072	0.058	0.025	0.094*
	(0.041)	(0.066)	(0.050)	(0.053)	(0.090)	(0.052)
Ownhouse	−0.092	−1.134*	−0.059	−0.188***	−0.305***	−0.071
	(0.061)	(0.077)	(0.096)	(0.058)	(0.055)	(0.088)
TV	0.092**	0.033	0.126**	0.155***	0.135**	0.169***
	(0.038)	(0.047)	(0.062)	(0.041)	(0.053)	(0.062)
Bike	0.061*	0.006	0.104**	0.088**	0.034	0.084*
	(0.033)	(0.037)	(0.044)	(0.035)	(0.047)	(0.044)
Fan	0.047	0.134**	−0.029	0.058	0.129**	0.021
	(0.039)	(0.053)	(0.051)	(0.043)	(0.063)	(0.061)
Natural Event	−0.020	−0.007	−0.030	−0.014	0.005	−0.039
	(0.042)	(0.052)	(0.058)	(0.051)	(0.052)	(0.062)
Age Child (months)	0.053***	0.025	0.078***	0.066***	0.031	0.096***
	(0.018)	(0.029)	(0.020)	(0.021)	(0.032)	(0.024)
Age Child squared	−0.0002***	−0.0001	−0.0003***	−0.0002	−0.000	−0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Backward Caste	−0.090***	−0.040	−0.141***	0.098**	0.094	0.088
	(0.032)	(0.043)	(0.045)	(0.045)	(0.058)	(0.068)
Hindu	0.151***	0.184***	0.147*	0.032	0.095	−0.020
	(0.049)	(0.058)	(0.081)	(0.060)	(0.062)	(0.098)
Telegu	−0.039	0.042	−0.117**	−0.086*	−0.066	−0.106**
	(0.033)	(0.035)	(0.050)	(0.044)	(0.068)	(0.049)
Education Father	0.004	−0.012**	0.016***	0.002	−0.011*	0.012***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)	(0.004)
Education Mother	0.004	0.008	0.001	0.009	0.005	0.008
	(0.005)	(0.007)	(0.006)	(0.006)	(0.009)	(0.008)
Household Size	−0.014**	−0.011	−0.019*	−0.011	−0.013	−0.007
	(0.007)	(0.009)	(0.010)	(0.008)	(0.011)	(0.010)
First Child	0.059	0.070	0.060	0.069**	0.091*	0.078*
	(0.036)	(0.052)	(0.048)	(0.032)	(0.045)	(0.042)
Region & Year FE	✓	✓	✓	✓	✓	✓
N. Obs	3,563	1,665	1,898	3,563	1,665	1,898
R-squared	0.056	0.072	0.095	0.062	0.100	0.121
F	12.08	42.05	40.72	16.70	42.53	111.94

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

Table A.6: OLS, Cognitive Outcomes - Standardised Scores

	Std. PPVT:			*Std. Math:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Exposure (months)	0.005**	0.007*	0.004	0.015***	0.017***	0.014***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)
Gender	−0.216***			−0.147***		
	(0.058)			(0.050)		
Rural	−0.186**	0.020	−0.347***	0.158**	0.266***	0.076
	(0.073)	(0.135)	(0.080)	(0.063)	(0.086)	(0.090)
Housing Quality 2nd quartile	0.013	−0.334	−0.048	−0.024	0.004	−0.036
	(0.048)	(0.075)	(0.055)	(0.034)	(0.045)	(0.053)
Housing Quality 3rd quartile	−0.082	−0.016	−0.150*	−0.020	0.050	−0.087
	(0.055)	(0.069)	(0.078)	(0.047)	(0.065)	(0.060)
Housing Quality 4th quartile	−0.062	−0.000	−0.101	−0.018	0.047	−0.054
	(0.052)	(0.064)	(0.075)	(0.071)	(0.110)	(0.095)
Ownhouse	0.075	−0.077	0.174**	0.087	−0.046	0.182**
	(0.061)	(0.093)	(0.086)	(0.057)	(0.088)	(0.067)
TV	0.103**	0.062	0.125**	0.018	−0.029	0.042
	(0.040)	(0.064)	(0.058)	(0.034)	(0.053)	(0.043)
Bike	0.087*	0.077	0.084	0.013	−0.068	0.074
	(0.052)	(0.054)	(0.077)	(0.055)	(0.089)	(0.055)
Fan	0.176***	0.206**	0.142*	0.251***	0.288***	0.221***
	(0.056)	(0.080)	(0.081)	(0.055)	(0.089)	(0.068)
Natural Event	0.010	0.090	−0.054	0.031	0.112	−0.045
	(0.070)	(0.101)	(0.093)	(0.052)	(0.085)	(0.056)
Age Child (months)	0.008	−0.010	0.021	0.026	0.046**	0.004
	(0.016)	(0.023)	(0.019)	(0.017)	(0.021)	(0.021)
Age Child squared	−0.000	0.000	−0.0001	−0.0001	−0.0001**	−0.000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00001)
Backward Caste	−0.092**	−0.096	−0.105*	0.010	−0.008	0.012
	(0.043)	(0.063)	(0.059)	(0.041)	(0.067)	(0.054)
Hindu	0.016	0.147	−0.101	0.213***	0.308***	0.114*
	(0.059)	(0.103)	(0.068)	(0.052)	(0.076)	(0.067)
Telegu	0.044	0.069	0.041	0.031	0.015	0.064
	(0.061)	(0.094)	(0.078)	(0.044)	(0.070)	(0.056)
Education Father	0.019***	0.018***	0.020***	0.015***	0.008	0.020***
	(0.005)	(0.006)	(0.07)	(0.005)	(0.008)	(0.006)
Education Mother	0.023***	0.021**	0.021**	0.034***	0.035***	0.032***
	(0.005)	(0.009)	(0.008)	(0.007)	(0.012)	(0.008)
Household Size	−0.013	−0.027**	0.003	0.015	0.002	0.030**
	(0.009)	(0.012)	(0.012)	(0.009)	(0.009)	(0.014)
First Child	0.105***	0.126**	0.095*	0.121***	0.136*	0.124***
	(0.036)	(0.050)	(0.051)	(0.036)	(0.070)	(0.033)
Region & Year FE	✓	✓	✓	✓	✓	✓
N. Obs	2,934	1,361	1,573	2,934	1,361	1,573
R-squared	0.118	0.130	0.112	0.154	0.163	0.172
F	29.65	71.83	65.58	34.24	60.91	134.49

*p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

Table A.7: Heckman Model, Health Outcomes - Standardised Scores

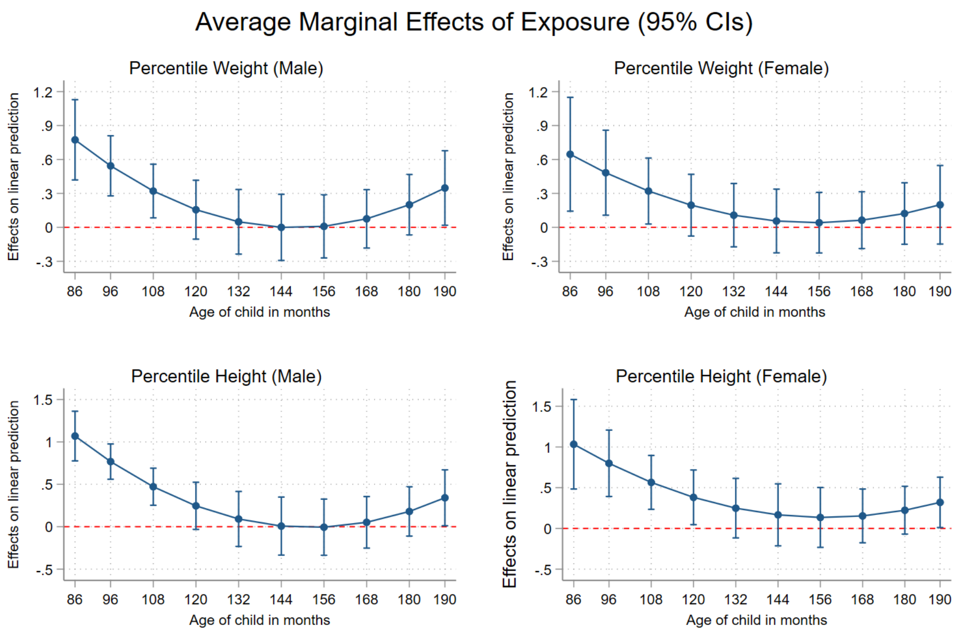
	Std. Weight:			*Std. Height:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Second Stage						
Exposure (months)	0.005***	0.006**	0.005*	0.010***	0.008**	0.012***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Mills Ratio	−0.032	−0.042	0.121	−0.003	−0.021	0.167
	(0.140)	(0.187)	(0.180)	(0.132)	(0.177)	(0.149)
Gender	0.021			−0.165**		
	(0.052)			(0.069)		
Rural	−0.270*	−0.258	−0.190	−0.056	0.089	−0.095
	(0.140)	(0.205)	(0.184)	(0.129)	(0.151)	(0.180)
Housing Quality 2nd quartile	0.016	0.038	0.007	0.057	0.110*	−0.007
	(0.032)	(0.054)	(0.045)	(0.040)	(0.057)	(0.061)
Housing Quality 3rd quartile	0.019	0.053	−0.034	0.053	0.072	−0.009
	(0.042)	(0.071)	(0.055)	(0.050)	(0.072)	(0.073)
Housing Quality 4th quartile	0.050	0.029	0.050	0.059	0.029	0.064
	(0.053)	(0.083)	(0.066)	(0.065)	(0.114)	(0.065)
Ownhouse	−0.094	−0.133*	−0.049	−0.188***	−0.305***	−0.057
	(0.061)	(0.076)	(0.103)	(0.059)	(0.060)	(0.096)
TV	0.097**	0.040	0.108*	0.156***	0.139**	0.145**
	(0.039)	(0.050)	(0.062)	(0.043)	(0.066)	(0.059)
Bike	0.060*	0.006	0.107**	0.088**	0.034	0.088*
	(0.034)	(0.038)	(0.047)	(0.035)	(0.048)	(0.046)
Fan	0.048	0.135**	−0.035	0.058	0.129**	0.013
	(0.039)	(0.053)	(0.050)	(0.044)	(0.063)	(0.064)
Natural Event	−0.021	−0.009	−0.027	−0.015	0.004	−0.034
	(0.042)	(0.056)	(0.058)	(0.049)	(0.054)	(0.064)
Age Child (months)	0.053***	0.024	0.080***	0.066***	0.031	0.098***
	(0.019)	(0.031)	(0.022)	(0.021)	(0.054)	(0.025)
Age Child squared	−0.0002***	−0.0001	−0.0003***	−0.0002***	−0.0001	−0.0004***
	(0.0001)	(0.0001)	(0.00001)	(0.0001)	(0.0001)	(0.0001)
Backward Caste	−0.091***	−0.037	−0.131**	0.097**	0.096	0.102
	(0.033)	(0.046)	(0.052)	(0.046)	(0.061)	(0.069)
Hindu	0.151***	0.184***	0.142*	0.033	0.095	−0.026
	(0.050)	(0.062)	(0.084)	(0.060)	(0.061)	(0.100)
Telegu	−0.038	0.043	−0.125**	−0.086**	−0.066	−0.116**
	(0.035)	(0.037)	(0.052)	(0.044)	(0.071)	(0.049)
Education Father	0.005	−0.011	0.015**	0.002	−0.010	0.010*
	(0.005)	(0.007)	(0.006)	(0.006)	(0.008)	(0.005)
Education Mother	0.005	0.009	−0.002	0.009	0.006	0.003
	(0.006)	(0.011)	(0.007)	(0.007)	(0.011)	(0.009)
Household Size	−0.112*	−0.011	−0.019*	−0.011	−0.013	−0.007
	(0.007)	(0.010)	(0.010)	(0.008)	(0.012)	(0.011)
First Child	0.062	0.073	0.051	0.070**	0.092*	0.066*
	(0.037)	(0.060)	(0.044)	(0.033)	(0.051)	(0.074)
Region & Year FE	✓	✓	✓	✓	✓	✓
First Stage						
Exclusion Restriction	1.005***	1.209***	0.757***	1.005***	1.209***	0.757***
	(0.217)	(0.374)	(0.277)	(0.217)	(0.374)	(0.277)
N. Obs	5,567	2,864	2,703	5,567	2,864	2,703
Selected	3,563	1,665	1,898	3,563	1,665	1,898

*p<0.1; **p<0.05; ***p<0.01
Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.

Table A.8: Heckman Model, Cognitive Outcomes - Standardised Scores

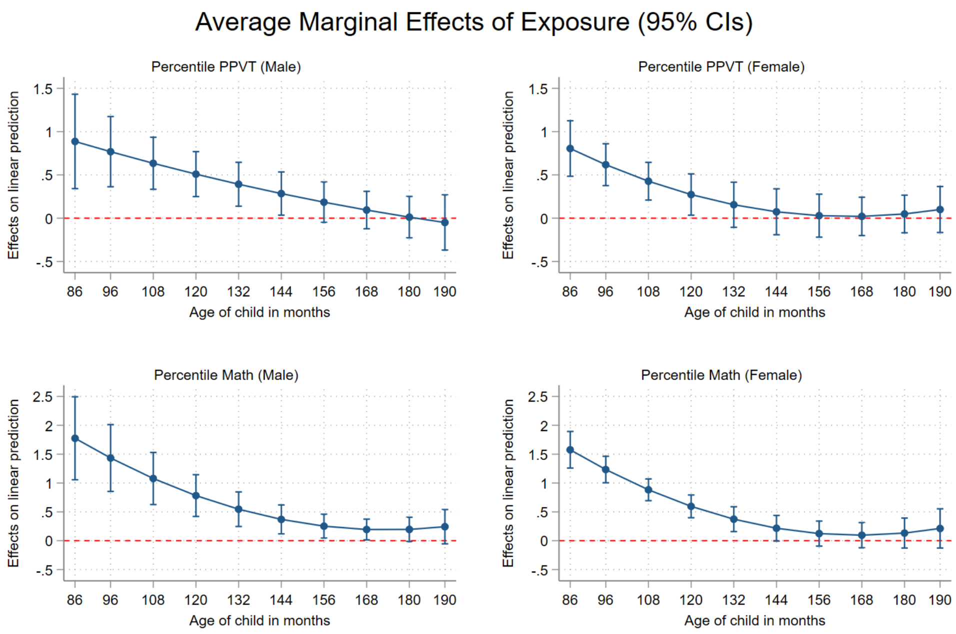
	Std. PPVT:			*Std. Math:*		
	All	**Male**	**Female**	**All**	**Male**	**Female**
Second Stage						
Exposure (months)	0.005**	0.007*	0.004	0.015***	0.017***	0.014***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)
Mills Ratio	0.147	0.064	0.286*	−0.005	−0.121	0.156
	(0.144)	(0.229)	(0.173)	(0.150)	(0.230)	(0.174)
Gender	−0.192**			−0.148**		
	(0.075)			(1.800)		
Rural	−0.098	0.056	−0.164	0.154	0.198	0.175
	(0.119)	(0.189)	(0.133)	(0.122)	(0.179)	(0.166)
Housing Quality 2nd quartile	−0.031	0.009	−0.058	−0.023	0.011	−0.041
	(0.059)	(0.086)	(0.059)	(0.038)	(0.053)	(0.056)
Housing Quality 3rd quartile	−0.101	−0.027	−0.176**	−0.020	0.071	−0.101
	(0.063)	(0.091)	(0.086)	(0.055)	(0.074)	(0.068)
Housing Quality 4th quartile	−0.097	−0.017	−0.164*	−0.016	0.079	−0.089
	(0.069)	(0.091)	(0.094)	(0.086)	(0.140)	(0.111)
Ownhouse	0.085	−0.078	0.209**	0.087	−0.046	0.199***
	(0.064)	(0.093)	(0.093)	(0.061)	(0.093)	(0.075)
TV	0.080	0.051	0.085	0.018	−0.008	0.020
	(0.049)	(0.087)	(0.068)	(0.041)	(0.064)	(0.052)
Bike	0.087*	0.077	0.086	0.013	−0.067	0.075
	(0.050)	(0.057)	(0.077)	(0.054)	(0.090)	(0.051)
Fan	0.173***	0.206**	0.132	0.251***	0.288***	0.215***
	(0.056)	(0.085)	(0.084)	(0.056)	(0.087)	(0.074)
Natural Event	0.012	0.091	−0.053	0.031	2.659	−0.044
	(0.071)	(0.104)	(0.097)	(0.051)	(0.085)	(0.056)
Age Child (months)	0.011	−0.010	0.026	0.026	0.045	0.007
	(0.071)	(0.027)	(0.023)	(0.018)	(0.024)	(0.025)
Age Child squared	−0.0000	0.0000	−0.0001	−0.0001	−0.0001	−0.000
	(0.00001)	(0.0001)	(0.0001)	(0.001)	(0.00001)	(0.0001)
Backward Caste	−0.090**	−0.100	−0.082	0.010	−0.001	0.025
	(0.042)	(0.067)	(0.059)	(0.041)	(0.080)	(0.055)
Hindu	0.011	0.146	−0.111	0.213***	0.311***	0.109
	(0.061)	(0.105)	(0.070)	(0.053)	(0.081)	(0.072)
Telegu	0.036	0.067	0.020	0.031	0.019	0.053
	(0.060)	(0.093)	(0.079)	(0.044)	(0.072)	(0.053)
Education Father	0.015**	0.015	0.015**	0.015***	0.012	0.017***
	(0.006)	(0.010)	(0.007)	(0.006)	(0.012)	(0.007)
Education Mother	0.019**	0.019*	0.013	0.035***	0.039***	0.027***
	(0.008)	(0.011)	(0.011)	(0.008)	(0.015)	(0.010)
Household Size	−0.014	−0.027**	0.003	0.015	0.002	0.030**
	(0.009)	(0.013)	(0.013)	(0.009)	(0.011)	(0.015)
First Child	0.009**	0.121**	0.072	0.121***	−0.263***	0.112***
	(0.042)	(0.059)	(0.061)	(0.038)	(0.075)	(0.036)
Region & Year FE	✓	✓	✓	✓	✓	✓
First Stage						
Exclusion Restriction	1.009***	1.254***	0.784***	1.009***	1.254***	0.784***
	(0.239)	(0.444)	(0.288)	(0.239)	(0.444)	(0.288)
N. Obs	4,826	2,506	2,320	4,826	2,506	2,320
Selected	2,934	1,361	1,573	2,934	1,361	1,573

*p<0.1; **p<0.05; ***p<0.01
Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels. Child controls: gender, age (months), being the oldest child, ethnicity, religion and language. Household controls: wealth, parental education, household size.



Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels.
Average treatment effect of exposure to Mid-Day Meal Scheme at different ages on health outcomes. Range from 86 (min) to 190 (max) months, any additional tick represents a year.

Figure A.1: Age Heterogeneity by Gender, Health Outcomes



Heckman two-step procedure; bootstrap standard errors (1500 replications) are clustered at district, gender and time levels.
Average treatment effect of exposure to Mid-Day Meal Scheme at different ages on health outcomes. Range from 86 (min) to 190 (max) months, any additional tick represents a year.

Figure A.2: Age Heterogeneity by Gender, Cognitive Outcomes