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Cognitive skills gaps in India: can (late) nutrition ameliorate them?

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Abstract

Using unique data from very young children in India, we estimate a value-added model of cognition. We use exposure to the Mid Day Meal Scheme interacted with a non-linearity in how birth year exogenously affects the probability of enrollment in public schools as an instrumental variable for nutrition. We find that a 1-standard-deviation (SD) increase in height-for-age at age 5 leads to cognitive test scores 11 to 14 percent of an SD higher at age 8. This result supports the recent literature on catch-up growth, particularly as effects are much larger for children who suffered from drought.

JEL Classification Codes: J13, J15, J24
Keywords: cognitive outcomes, nutrition, children and test score gaps.

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1 Introduction and Literature Review

Though a general consensus may be arising from different strands of the literature regarding the critical nature of early life investments (Shonkoff and Phillips, 2000), particularly for cognitive skills (Sameroff et al., 1993), and the case for early investments (Nores and Barnett, 2010; Engle et al., 2011; Walker et al., 2011; Akresh et al., 2012; Barham et al., 2013), significant uncertainties prevail regarding the type and timing of the interventions to be most effective. An emerging empirical literature finds positive average impacts for programs aimed at improving nutrition during early childhood on a range of short- and long-term outcomes (Walker et al., 2011).[1] Particularly, nutritional investments in the first 1,000 days[2] have been shown to be one of the most important predictors of later cognitive development in developing countries. However, this evidence comes mostly from one influential, although small-sample, long-term longitudinal study in Guatemala (Victora et al., 2008; Hoddinott et al., 2008; Behrman et al., 2009; Maluccio et al., 2009; Martorell et al., 2010); and more recently from the evaluation of a conditional cash transfer in Nicaragua (Barham et al., 2013). Using the Young Lives longitudinal data (YL)[3], Sanchez (2009) and Outes et al. (2010) also document a positive relation of 0.20-0.37 standard deviations (SDs) between nutrition at age 1 and cognition at age 5 in Peru.

From a policymaking perspective, it is often claimed that (i) growth failure and the resulting cognitive deficits are reversible only at great costs after about 2 years of age, and (ii) health and nutritional interventions directed toward older children may not be effective (Martorell et al., 1994; Checkley et al., 2003). Consequently, decisions about where to invest scarce development resources are often made on the assumption that the window of opportunity closes after 2 years of age. Recent evidence from multiple settings, however, challenges the categorical assumption that there is no catch-up growth after the first 1,000 days

[1]Non-experimental studies from Zimbawe (Alderman et al., 2006), Jamaica (Walker et al., 2007) and the Philippines (Carba et al., 2009) show the importance of stunting for long-term outcomes such as school enrollment, employment and psychological function. However, these datasets do not have cognitive development measures at young ages to include as a control in the estimation.

[2]The 1,000 days are defined in the nutrition literature as 9 months in utero plus 24 months of life; or roughly 1,000 days.

[3] These data consist of two cohorts of children (the "younger" and the "older") surveyed over three rounds four years apart (Round 1 in 2002, Round 2 in 2006, and Round 3 in 2010). We use the Younger Cohort that spans data from 6 months to 8 years of age. See www.younglives.org.uk.

and that the window of opportunity for nutritional investments is closed when children become 2 years old (Johnson 2002; Crookston et al., 2010, Outes-Leon and Porter, 2012; Singh et al, 2013). In fact, studies of children suffering from prenatal or postnatal undernutrition demonstrate that it is possible to recover from early growth deficits and – more central to this paper – to experience improved cognitive outcomes well beyond the first 2 years of life (Crookston et al., 2011, Barnham et al., 2013). However, most papers do not look at cognitive outcomes, and while in the case of Crookston et al. (2011), only correlations are provided, in the case of Barham et al. (2013) the catch-up was possible for anthropometrics but not in cognitive outcomes.

Therefore, the main objective of this paper is to fill an important gap in the literature by investigating the potential for returns to investments in nutrition after the first $1,000$ days in India, the country ranked first in the world for malnutrition (Arnold et al., 2009).[4] To the best of our knowledge, this is the first study using panel data and a value-added production function of cognitive skills to study the relation between nutrition (height-for-age, [HAZ]) at age 5 and cognition (receptive vocabulary scores as measured by the the Peabody Picture Vocabulary Test, [PPVT]) at age 8 in India.

We look specifically at how socioeconomic [SES] gradients in early cognition outcomes are mediated by nutrition. Divisions by SES in India are defined according to whether a household belongs to a certain caste. Gang et al. (2008) find that differences in educational attainment explain about 25 percent of the poverty gap between both the Scheduled Caste and Schedule Tribe (the so-called Lower Caste [LC]), composed of the Scheduled Castes [SCs] and Scheduled Tribes [STs], and non-Scheduled Hindu households (Upper Caste [UC]). For further information on castes, see the appendix.

For this investigation, we exploit the novel measures of cognitive outcomes, anthropometrics, and other rich measures provided in the YL data.

Furthermore, the methodology used here allows us to go beyond previous empirical studies. We follow the spirit of Todd and Wolpin (2003, 2007) and Cunha and Heckman (2007), who model cognitive skills as a function of the child's innate

[4]In India, 48 percent of children younger than age 5 exhibit stunting, according to the Indian National Family Health Survey (NFHS3). This level is 20 times higher than would be expected in a healthy, well-nourished population.

genetic ability and the cumulative effect of present and past investments. This structural production function analysis makes considerable progress in identifying nutrition's causal effect on cognitive outcomes. The challenge in estimating this relationship is that other inputs are missing. And unobserved child, parental or household-specific factors may affect both nutrition and cognitive outcomes, which may lead to a correlation even though no causation exists.

Unlike previous research, we attempt to account for all of these issues as follow: First, the contribution of all unobserved previous inputs and past endowments is resolved with our value-added specification. Second, the endogeneity of HAZ is explicitly considered with an instrumental variable [IV] approach. We argue that we ameliorate the identification problem by using the IV. The instrument is the interaction of the exposure to the Mid Day Meal Scheme [MDMS] in India, which seemingly affects nutrition, with an indicator for whether the child was born in 2001, which exogenously affects enrollment in school (where the program operates).

The cutoff date for enrollment stated in clause 14 of the Andhra Pradesh public school system[5] plus the fact that there is an extended time for admission of 3 months, produces an exogenous discontinuity in enrollment between December and January of the academic year because of exogenous variation in birth years of children in the sample. Moreover, even if this cutoff in the eligibility criterion for school was poorly enforced (as anecdotal evidence shows), a recent paper (Singh et al., 2013) argues that a change in the calendar year of birth strongly affects the probability of enrollment as parents use it as a rule of thumb to determine the appropriate time for enrollment. We also run an important robustness check in which we use only those children born closer to the cutoff date for the estimation. Results are strengthened as a result of this new sample. Moreover, we find heterogeneous effects as our coefficient of interest doubles to 0.24 SD for children whose families suffered from drought.

In brief, we find strong evidence that better nutritional status beyond the first 2 years of life leads to better cognitive outcomes at age 8.

Using a specification that incorporates these features, we find that the predicted

[5] "[...]eligible for public school is a child who has completed five years of age as on 1st September of the year of admission [...]". Similarly, the clause states that "[...]all children turning 4 before Sept 1st-December 30th of the year preceding the school year will be accepted for enrolment [sic] in public schools[...]"

PPVT score gaps between UC and LC would be reduced by 26 percent if we compensate LC children with low HAZ with the average level of HAZ observed for UC children. It is interesting to note that the gap between UC and LC for boys is closed by relatively less when equalizing HAZ (one-fifth of the gap), while for girls about half of the gap would be closed by leveling nutritional status. Our data also show evidence of pro-male discrimination in both UC and LC castes. However, as UC families seem to be discriminating more against their daughters, any policy directed to level the playing field in nutrition or other inputs will need to take into account this discriminatory parental behavior and direct more resources to girls in UC homes.

Overall, our results seem to indicate that nutritional interventions (acting on HAZ, even later than the 1,000 days, and particulary for children whose families have been affected by shocks), as well as stimulation interventions (acting on the PPVT score at age 5), could be promising given the magnitudes of the effects found in this paper. However, policies that acknowledge the disadvantages of LC children and the differential treatment of girls vis a vis boys are also needed.

This paper proceeds as follows. The second section describes the methodology for modeling the production function and considers its empirical application and challenges. The third section provides details on the data and our instrumental variable, while the fourth section presents estimates of the cognitive skills production function, the robustness check, and the caste disparities in test scores. The last section concludes.

2 Methodology

2.1 Economic Framework

As a guide to our empirical analysis, we set up a model of household production and time allocation. The model follows the spirit of Todd and Wolpin (2003, 2007) and Cunha and Heckman (2007), but we focus on the choice of parental investment to produce child's human capital as well as child's nutrition. We assume that parents intertemporally maximize utility derived from consumption (c), leisure (l), and their child's cognitive skills (θ) by choosing how many hours to work (h), family inputs for the production of cognitive skills (i), and the family nutrition inputs (n):

$$max_{h_t,i_t,n_t} \sum_t U(c_t, l_t, \theta_t) \tag{1}$$

subject to: a production function of cognitive skills (θ_t) that depends on the stock of cognitive skills at the beginning of the period (θ_{t-1}), parental investment (i_t), the child's nutritional status at the beginning of the period (H_{t-1}), family characteristics (X_t), and the child's endowments (μ_t):

$$\theta_t = f(\theta_{t-1}, i_t, H_{t-1}, X_t, \mu_t), \tag{2}$$

and a production function for the next-period nutritional status:

$$H_t = g(H_{t-1}, n_t, X_t, \mu_t) \tag{3}$$

We assume that it takes time to build nutrition and therefore investment in nutrition affects the child's nutritional status only at the end of the period t and therefore does not affect cognition at t. This assumption implies that cognition at t is affected only by investments in nutrition made in period *t-1* (n_{t-1}), thus ruling out contemporaneous effects from nutrition to cognition. In our empirical specification, this will translate to investments in nutrition at age 5 only affecting children's cognition at age 8 and beyond.

We also have a time constraint, where h are the total number of hours worked and l is leisure:

$$l_t = 1 - h_t, \tag{4}$$

and a budget constraint,

$$wh_t = c_t + p_i i_t + p_n n_t. \tag{5}$$

Given wages and prices, parents choose how much to work in the market, how much to invest in their child's production of cognitive skills, and their child's nutrition.

2.2 Empirical Strategy

Our goal is to estimate equation (2) and identify the relation between nutrition and cognition in early childhood in India. In doing so, we start by taking a step backward and estimate a contemporaneous version of the production function of cognitive skills. We use this specification as a benchmark and then focus in a richer value-added specification.

2.2.1 The contemporaneous specification

The contemporaneous specification relates cognitive skills of child i with family inputs in period t (i_{it}); nutrition at the beginning of period t (H_{it-1}); other child, family, and community factors in period t (X_{it}); and the child's endowment (μ_{it}). Empirically, we also allow for an additive error, which results in

$$\theta_{it} = \alpha + \gamma H_{it-1} + \vartheta i_{it} + \delta X_{it} + \beta\, \mu_{it} + \varepsilon_{it}. \tag{6}$$

The problems of the contemporaneous specification are well known. As Todd and Wolpin (2003) point out, this specification would be justified if only contemporaneous inputs matter for the production of current cognitive skills or inputs are unchanging over time, so that current inputs capture the entire history of inputs. Additionally, we would need to assume that contemporaneous inputs are unrelated to unobserved endowment and the additive error (which accounts for omitted inputs and measurement error). This last assumption is inconsistent with the model just specified or any other economic model of optimizing behavior in the spirit of Becker and Tomes (1986), where parents care about their child's human capital.

Even though the contemporaneous specification might be informative when very limited data are available, more flexible specifications allow us to estimate the production function under milder assumptions. We now describe a more robust value-added specification.

2.2.2 The value-added specification

In its most common form, the value-added production function of cognitive skills adds a relationship between current skills and lagged cognitive skills to the contemporaneous specification. It can be written as

$$\theta_{it} = \alpha + \gamma H_{it-1} + \vartheta i_{it} + \delta X_{it} + \varsigma\theta_{it-1} + \beta\,\mu_{it} + \varepsilon_{it}. \tag{7}$$

Note that if lagged cognitive skills is a sufficient statistic for input histories and unobserved endowment, estimating (7) would yield consistent estimates of the production function of cognitive skills. However, we need to assume that the rate of decline must be the same for all inputs, and the impact of endowment decline geometrically at the same rate as input effects. In other words, given the assumptions here, our lagged cognitive skills controls for both the unobserved endowment (i.e., genetics) of the child and home and school input histories. Following Harris and Sass (2011), we further assume that lagged cognitive skills follows a Markov process and is uncorrelated with the error.[6] Given these assumptions, current PPVT becomes a linear function of prior PPVT, contemporaneous student, family and schooling inputs, and an specific constant. The fact that lagged PPVT controls for past school and parental inputs is crucial for our identification strategy (see later section "Exclusion Restriction").

2.2.3 Endogeneity of child nutrition

A common problem in the production function approach to studying childhood outcomes relates to endogeneity of particular regressors, such as nutrition or home inputs. Particularly, since parental preference for child quality and a child's genetic endowment are unobserved, Ordinary Least Squares (OLS) estimations of the nutrition-cognition nexus, as well as the parental investment-cognition nexus, are likely to be biased.

If a child's endowment is malleable, μ_{it} represents factors such as innate ability in addition to motivation and the child's effort, which are out of the parents' control but are influenced by the home environment and genetics (Rosenzweig and Wolpin 1988). According to our model, the level of investments in each

[6] Without this assumption, lagged cognitive skills would be endogenous and OLS estimation would potentially be biased. Moreover, we will have complementarity between past PPVT and past HAZ which would also lead to biases. Alternatively, one could estimate IV models by assuming there is a higher-order degree of serial correlation in the residuals and using twice and greater lags of the PPVT score as instruments for prior-year PPVT. Given that our cognitive skills data begin before children go to school, such an approach is infeasible.

period is responsive to the child's endowment. This introduces an endogeneity bias that can be either positive or negative. Consider the case of family inputs: On the one hand, it could be that parents, observing that their child is of high endowment, expect a higher return on their investment and so invest more in him. In this case, there would be a positive correlation between child's endowment and the amount of inputs. On the other, it could be that parents who observe that their child is of low endowment try to compensate by investing more inputs. This type of behavior would induce a negative sample correlation between child's endowment and the amount of inputs. We expect the latter bias to predominate – that is, there is a downward bias in the OLS coefficient due to a well-documented fact in India of compensatory behavior of parents of low-endowment children or children subject to shocks (Attanasio et al., 2013).

Another challenge in the estimates arises from the fact that parental preferences might affect the level of investment. For example, parents with a strong preference for child investments will provide their children with inputs that improve both their childs nutritional status and cognitive skills.

As mentioned in Section 2.2.2, the value-added model assumes that the impact of endowment must decline geometrically at the same rate as inputs. Under this assumption, estimates will be unbiased. However, because parental preferences or parental learning about the child's unobserved endowment might not be completely captured in the last-period test score, the coefficients on nutrition and other investments can still be contaminated. Our specifications will then include a rich set of controls for family and non-family characteristics to deal with common factors across families that could determine investments in their children. And to partly solve the problems in the coefficient of nutritional status we assume that nutritional status at the end of the previous period is what affects the child's performance on the cognitive test. The child's motivation and effort in t are not correlated with his nutrition achieved last period given our timing assumption in equation (3). Thus, the timing assumption ameliorates potential endogeneity bias because nutrition is set at the beginning of the period and cannot therefore be altered by the child's motivation, strength and effort in the current period. We go even further exploring potential endogeneity bias in our parameter of interest and instrument nutritional status at age 5 with a dummy that represents exposure to the MDMS interacted with an indicator for whether the child was born in 2001. We detail the validity of the instrument in the next section.

3 Data

3.1 General Description

In this study, we focus exclusively on the younger cohort of children of the YL project.[7] We use data from three rounds of the Andhra Pradesh (AP) survey. In Round 1 (in 2002) 2,000 children 6 to 18 months of age were surveyed. Round 2 tracked the same children and surveyed them in 2006 at age 5 and Round 3 surveyed them in 2010 at age 8. The children in our sample were actually born during an 18-month period from January 2001 to June 2002. The attrition rate was only 3.9 percent overall, which is very low for a study of this size. In terms of the representativeness, despite a few biases (see Kumra (2008) in a note comparing the YL survey with the Demographic and Health Survey, DHS), it is shown that the YL sample in Andhra Pradesh covers the diversity of children in the country.

The stratified cluster sample is both region and caste representative; and the estimation used in this study incorporates the YL survey design by using regions as the stratification variable and the sentinel sites as the clustering variable.

3.2 Description of Key Variables and the Instrument

We focus on one test, the PPVT, which is a test of vocabulary recognition that has been widely used as a general measure of cognitive development. The PPVT is measured at age 5 and at age 8 for the same children. In the model in the previous section, t = 8 years of age and t-1= 5 years of age.

Since it is difficult to assume that people responding to a vocabulary test in different languages could be compared, the analysis for the PPVT is restricted

[7] The sampling scheme adopted for YL was designed to identify interregional variations with the following priorities: (i) a uniform distribution of sample districts across the three regions to ensure full representation, (ii) the selection of one poor and one nonpoor district from each region; and (iii) when selecting poor districts and mandals (i.e. city areas), consideration was given to issues that might affect childhood poverty, including the presence or absence of the AP District Poverty Initiative Programme (APDPIP).

to the 90 percent of children who answered the PPVT test in Telugu (the second most common language spoken in India). Throughout the study we obtained consistent results using this sample compared with (i) the full sample or (ii) the full sample with inclusion of a statistical control for whether the respondent spoke the test language since birth.

The rationale for the use of the height-for-age z-score (HAZ) is that a deficit in the height-for-age measure until age 2 corresponds to the inability to reach the genetic potential in terms of height. Children with a HAZ below 2 SD of the mean of the reference group are defined as stunted in the literature. The HAZ is then viewed as a longer-term measure of deprivation than weight-for-height, which is more sensitive to short-term or seasonal variations in food availability. We expand this interpretation until the age of 5 following the recent literature on catch-up growth and take the HAZ measured at age 5 (based on 2006 World Health Organization [WHO] standards) as our main independent variable of interest.[8] Height is also reported to have a strong relationship with mental function and mortality.

As measures of parental inputs we include whether the child went to a preschool; whether the preschool was public, private, religious or run by a Non-governmental organization [NGO]; whether the child currently goes to school; and whether the school is public, private, religious, or run by NGO.[9] In an alternative version of the regressions, we used family income as a proxy for parental inputs.

Finally, our control variables refer to the child, caregiver, father, home characteristics, and geographical dummies. Child characteristics are gender, age in months, birth order, and caste. Caregiver characteristics refer to the years of education completed.[10] Father's education is also included as a control. Home characteristics such as household size, whether the family is a recipient of a social program, whether the household is located in an urban or rural area and their wealth index (Filmer and Pritchett 1999), are also included. The wealth

[8] see www.who.int/growthref/

[9] We also tried specifications with parental inputs more related to educational expenditures on the child as fraction of family income. The main results remain unaltered, but sample sizes reduces significantly to a fifth of our current sample. Therefore, we only used these measures for an auxiliary analysis in the counterfactuals section 4.4 when we quantify the role of different components on cognition gaps.

[10] In a robustness check regression, we also included the number of antenatal care visits and whether the mother was given iron folate tablets during pregnancy (not reported).

index has three components: housing quality, consumer durables, and services. Geographical dummies included are Coastal Andhra and Rayalaseema (with Telangana as the base category), as well as village (sentinel sites) dummies.

3.2.1 The instrument: the Mid Day Meal Scheme and the exogenous discontinuity in enrollment

As explained in subsection 2.2.3, we need an instrument to deal with potential biases from our estimation.

In November 2001, the Supreme Court of India directed the government to provide cooked mid day meals consisting of no less than 300 calories and 8-12 grams of protein in all public primary schools (the so called MDMS program). By 2003, most states had started this provision and the state of Andhra Pradesh fully introduced it in January 2003 (Dreze and Goyal, 2003), coincidentally, the year after the YL survey started in AP. In later years, Thorat and Lee (2005) and Pratham (2007) report that over 98 percent of government schools in AP were serving a meal on the day of their school survey. The program was premised on expectations of significant gains in nutritional outcomes among school children.

Hence, following Singh et al. (2013), the MDMS dummy variable is defined as all children currently attending public school. Importantly, the age of children in Round 2 was exactly around the normal time of school enrollment; as we later discuss, this is critical to our identification. In our data, only 10 of 682 caregivers reported that their school does not provide a mid day meal, thus confirming the widespread implementation of the program indicated by previous studies.

The second element in our IV is related to the cutoff date for enrollment in clause 14 of the Andhra Pradesh public school system, stating that a child who has completed five years of age as of September 1st of the year of admission is eligible for public school. Moreover, the fact that there is an extended time (3 months) for admission, produces an exogenous discontinuity in enrollment between December 2005 and January 2006 because of exogenous variation in the year of birth of children in the sample (See Figure 1 and also Figure A.1 for the timeline of relevant events in our data).

We could have used only the dummy for whether a child was born in 2001 as the instrument itself; however, this would not give us a strong enough first stage

(Angrist and Krueger, 1991). Therefore, our IV is the interaction of MDMS with an indicator variable for being born before December 2001 (MDMS*Born in 2001). The intuition is as follows: The MDMS program strongly predicts HAZ at age 5 (Singh et al., 2013)[11] but does so particularly for those children born in 2001, who are the ones most benefiting from the meals as they are more likely to be in school (and these meals are served in school). The treatment group will then have enjoyed an average of 9 more months of meals than our control group at the time of the second survey (with a minimum of 7 months and a maximum of 1 year).[12] In an important robustness check, instead of comparing all children born in 2001 with all children born in 2002, which could differ for reasons such as season of birth, climate issues, among others, we compare children closer to the cutoff date–namely, children born in November and December 2001 with those born in January and February 2002 (sample sizes are too small to consider only December against January).

Self-selection into the program A major concern related to nonrandom program placement is the endogeneity of treatment (enrolling in a public school), especially via self-selection into the program. It is possible that self-selection into public schools is correlated with anticipated benefits of the program as reflected in changes in health or learning over time. Parents could have been influenced by the MDMS in deciding whether and at what age to enroll their children in public schools. Self-selection can take place through multiple mechanisms reviewed in Singh et al. (2013). The channel most likely to be influential is that parents can decide to enroll their child in a public school at a younger age than they otherwise might to benefit from the program meal.

Most of the children who were not yet in school in the second round would join formal schooling soon.[13] The survey therefore also asked the caregivers of

[11]Using YL data, Singh et al. (2013) showed that the access of 4 to 5 and 1/2 year-olds to the MDMS between mid-June 2006 (the beginning of the school year) and the time of the survey in 2007 had a direct impact on children's HAZ, with large and significant gains in HAZ for children whose families suffered from drought.

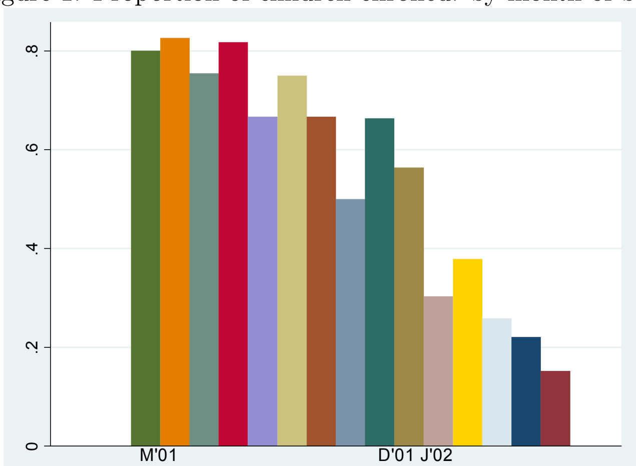
[12]Afridi (2010) relies on built-in randomness in whether a child's 24-hour food consumption recall was for a school or non-school day in India. She finds that the daily nutrient intake of MDMS participants increased substantially; namely, the daily protein deficiency and the calorie deficiency of a primary school student decreased by 100 and 30 percent, respectively. This proves there was no crowd-out of nutrition at home, which is also an important part of the identification strategy.

[13]About 50 percent of the children in our sample were in formal school by the second round and another 20 percent in informal schooling. Of those attending formal schools, 79 percent

children not yet in school what type of school their child would likely attend and the age at which they thought the child would be enrolled. The caregivers of over 95 percent of the children not yet enrolled report that they expected the child to be in school by the age of 6 years.

In our paper, we use the information on the type of school that children will attend in the near future to restrict the comparison group to children who are not currently enrolled but will be enrolled in a public school in the near future. We then compare children currently in public schools – and therefore recipients of the MDMS (N=609) – with children who will go to public schools in the future (N=438). This allows us to abstract from the endogeneity of the choice between private or public schooling.[14] This results in losing 24 percent of the sample due to their attendance at private, NGO, or religious schools.

Figure 1: Proportion of children enrolled: by month of birth



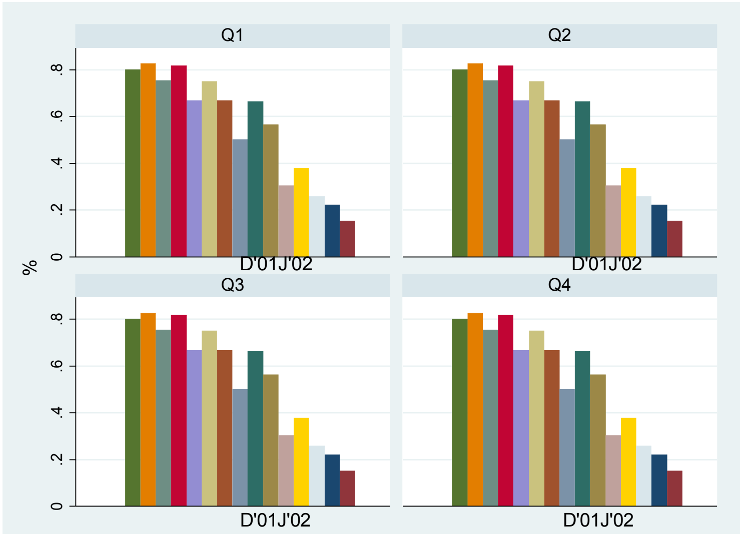
Source: Authors calculations based on YL data.

To further address endogeneity caused by self-selection, we exploit the non-linearity in the relationship between age and enrollment induced by a change in the calendar year of birth. Figure 1 shows an increasing rate of enrollment as children age and a sharp discontinuity (a jump) in mean enrollment from around 72 percent for children born in 2001 to less than 30 percent for children born in 2002. The jump ranges from 57 percent for children born in December 2001 to

were in public schools and the rest were in private schools (including those run by NGOs and religious charities).

[14]Table 1 of the paper by Singh et al. (2013), shows that differences between treatment and comparison group are small and not significant.

Figure 2: Proportion of children enrolled: by month of birth and wealth quartile



Source: Authors calculations based on YL data.

30 percent for children born in January 2002. More importantly, Figure 2 shows that the discontinuity holds for every quartile of wealth. The latter finding is reassuring as this means that richer families, seemingly more informed, caring, and motivated about their childs development, are indeed also following state rules on enrollment or (as Singh et al. (2013) argue) the rule of thumb.

Given the lack of full compliance with the cutoff for enrollment (i.e., 30 percent of children born in 2001 were not in school while around 30 percent of those born in 2002 were indeed in school), we explored variables the age at which caregivers of children born in 2001 and 2002 were expecting their child to be in school: this figure was not significantly different between the two groups. Also not significantly different was the main reason (i.e., the school was near the home) caregivers chose the specific school for their child to attend. Examining the reasons some of the children born in 2001 might start school later was not helpful because most parents stated “other reason” (54 percent).

Exclusion restriction We are aware that only some of the determinants of MDMS participation are exogenous (those determined by calendar year of birth) as the variable itself is not excludable in the manner required for a valid IV. However, given our structural assumptions in which all the missing past unobservable inputs (from parents and from school) are captured by the lagged PPVT (Todd and Wolpin, 2003, 2007; Harris and Saas, 2011), we argue that the exclusion restriction is respected as there is no reason to believe the MDMS had a direct effect on cognitive development at age 8 beyond its effects on nutrition (the instrumented variable) and on the PPVT at age 5.[15]

Violating the exclusion restriction requires a factor that affects PPVT at age 8, not via PPVT at age 5 or via nutrition. For instance, one could think that the MDMS might have increased concentration in class and therefore (speed of) learning due to the reduction of "classroom hunger". However, given our value-added specification and the timing of the test (see Figure A.1 showing that most children are exposed to school long before the Round 2 survey collects data on the PPVT), this learning effect should be entirely captured by the coefficient of past PPVT.

One could also think that children who are in school at age 5 are more likely to be in school at age 6, which will also affect the PPVT at age 8 via more accumulated learning. However, this is not a likely channel as school enrollment at ages 6 to 8 is already at 100 percent. Another possible channel is that children in school at age 5 will acquire more socialization skills and will be more able to "sit still", which can then affect their performance on the PPVT at age 8. This could be a likely channel if the difference between treatment and control groups were large enough, but we believe it is quite unlikely that a few more months of school attendance will influence socialization skills.

A last possible channel is that more meals at age 5 will make the child stronger and taller at ages 6 to 8 (but not via HAZ at age 5),[16] which by itself could influence the next-period PPVT. However, we could not find any paper in the economics, child development, or the medical literature that makes this channel plausible.

The exclusion restriction on the IV would also be violated if a change in the calendar year of birth had a nonlinear impact in this age range, not only on the probability of enrollment but also on the changes in the PPVT. The results of Singh et al. (2013) indicate that the benefit of the meal program is concentrated on children in families affected by drought. Any general nonlinear effect of age

[15]Todd and Wolpin (2003) claim that inputs reflect all choices made by parents and schools.

[16]This channel is inspired by the fetal programming literature. See Barker (2004).

should not be confined to the impacts of the scheme on drought-affected children but on the entire group of beneficiaries as a whole. Furthermore, the children in the enrolled and non-enrolled groups are very close in mean age (as far apart by 2 months on average) and our PPVT z-scores are norm-referenced by age measured in months. Therefore, we do not expect year of birth to have a nonlinear effect.[17]

3.3 Descriptive Statistics

We now use seven-month moving averages of the internally standardized PPVT and split the sample into two groups of children: those in the UC and those in the LC. We further split the sample by gender. The upper panel of Figure 3 shows age patterns in the caste gradients in child development, while the middle and bottom panels show these patterns by gender (UC in the left panels and LC in the right panels). The top panel shows: First, by age 5, the majority of differences between castes are already apparent. The z-scores of the UC children are 0.20 to 0.30 SDs (by looking at the figure and drawing a horizontal line at the level of a 67-month-old LC, a 6-month delay in language development can be estimated) greater than those in the LC children. Second, gradients apparent among 4- to 5-year-old children seem to widen as these children enter the first years of primary school in Round 3 (i.e., the difference between castes increases to 0.50 SD). UC children maintain and even improve their vocabulary throughout primary school. The left figure in the middle panel shows UC females have z-scores consistently higher than those of their male counterparts at age 5 years. Conversely, z-scores for 5-year-old LC females are consistently worse than those of LC males. Finally, the bottom panel plots the same relation for 8-year-old children. The reversal of the lines in the left figure shows that the UC females perform considerably worse than their male counterparts. The z-scores for 90-month-old UC males is around 0.70 SD larger than the z-scores for females of the same age.

Figure 4 shows the same analysis but for HAZ. These scores differ from

[17]It has to be noted that there is a cost to our strategy: at least part of the MDMS "effect" on cognition will be captured by the lagged PPVT score since (a) children have been in school for an extra academic year and (b) any effects of improved nutrition in 2007 should also be apparent on PPVT in 2007.

the internally standardized PPVT z-scores, as they are externally standardized scores; that is, YL uses the WHO standards with respect to a reference group of healthy children for the standardization. The deficits are very important: By the time children are 5 years old, lower (upper) caste children are 2 SD (1 to 1.5 SD) behind the reference healthy population (which places the average LC child in the "stunted" category). The nutritional status of UC children seems to be worsening over time in Round 2, while in Round 3, these gaps remain significant but there is neither worsening nor catch-up.[18]

The means and SDs of all relevant variables are presented in Table 1. The first column presents results for the full sample, the second column for LCs (composed of SCs and STs), the third column for Backward Castes (or BC),[19] and the fourth column for UCs. The last two columns show p-values for the difference of means between LCs and BCs, and UCs and LCs, respectively (the latter are the most relevant comparison for this paper).

The state of AP has achieved progress on many indicators since the mid-1990s. However, even though LCs and BCs have become wealthier and increasingly urban, Table 1 shows that significant differences remain based on sector (rural versus urban), caste, and region. Over time, all castes and cohorts are becoming richer, but as inequality did not decrease substantially, it seems that UCs benefit more from growth. UC mothers[20] have about two more years of schooling than BC and LC mothers, averaging a total of about 3.5 years of education completed in Round 2 (the latest available for this variable). For fathers, the differences between castes are similar, but UC fathers average a total of 5.5 years of education.

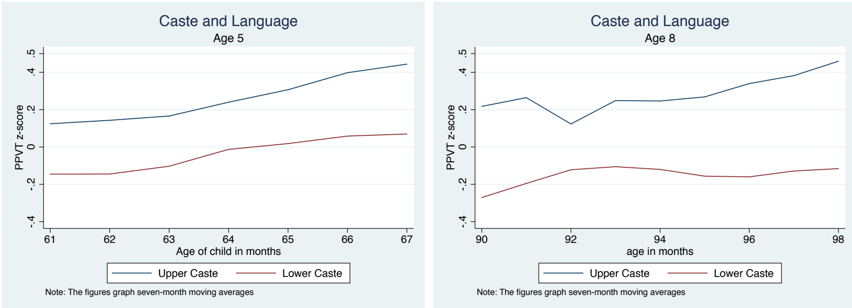
Another important predictor of children's success is parental nutrition, and a good proxy at hand in YL data is the caregiver's height: As expected, LC mothers are, on average, 2 cm shorter and 7 kilos lighter than UC mothers (not

[18]Table 1 shows that even if the level of stunting decreased over time for all groups in AP, currently 41 percent of children 5 years of age are stunted, which is less than the national average of almost 50 percent.

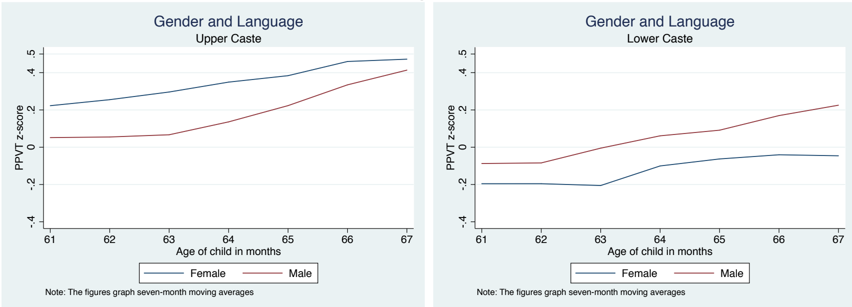
[19] There is no consensus in the literature on whether to explicitly treat this category as a separate social group. Jenkins and Barr (2006) and Dreze and Kingdon (2001) consider SCs and STs as separate from Backward Castes (BCs) on the grounds that completion rates are much lower than for other groups. We have therefore separated out this group and explicitly controlled for BC membership in the results section. We have also further split the LC group between SC and ST.

[20] In this sample 98.5 percent of the caregivers are the biological mothers.

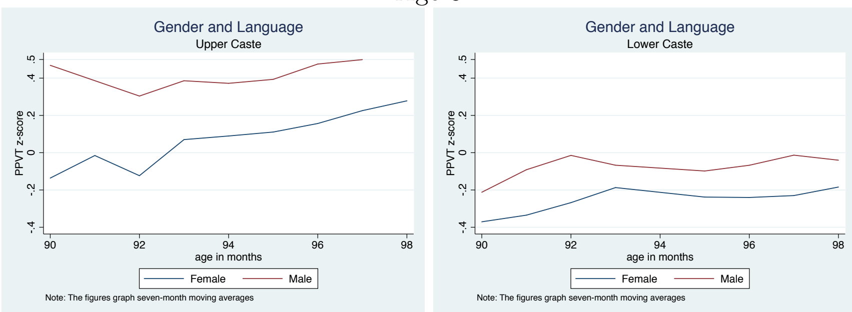
Figure 3: Panel data analysis of PPVT age patterns: ages 5 and 8



Age 5

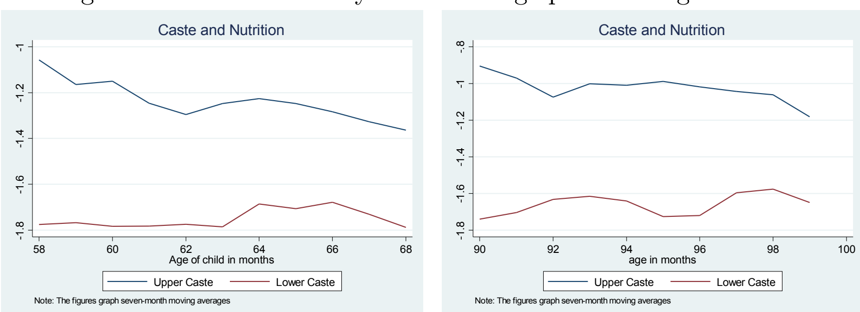


Age 8



Source: Authors calculations based on YL data.

Figure 4: Panel data analysis of HAZ age patterns: ages 5 and 8



Source: Authors calculations based on YL data.

Table 1: Means and T-tests of main variables by caste

	Total	LC	BC	UC	T-test (P-value) LC-BC	LC-UC
	(1)	(2)	(3)	(4)	(5)	(6)
Child						
Cognitive scores						
Round2 PPVT	35.420	40.479	31.465	36.098	0.000	0.195
Round2 PPVT (z-score)	-0.203	-0.047	-0.325	-0.182	0.000	0.195
Round3 PPVT	53.069	53.737	51.167	60.431	0.135	0.026
Round3 PPVT (z-score)	-0.174	-0.153	-0.236	0.065	0.135	0.026
Individual characteristics						
Round2 Child age (months)	64.451	64.231	64.530	64.912	0.228	0.103
Round3 Child age (months)	95.587	95.477	95.535	96.304	0.814	0.050
Born 2001	0.722	0.737	0.698	0.712	0.197	0.386
Round1 Last-born	0.490	0.519	0.469	0.490	0.133	0.608
Scheduled Caste	0.236	0.607	0.000	0.000		
Scheduled Tribe	0.153	0.393	0.000	0.000		
Backward Caste	0.514	0.000	1.000	0.000		
Upper Caste	0.097	0.000	0.000	1.000		
Round3 Coastal Andhra	0.374	0.396	0.361	0.363	0.272	0.544
Round3 Rayalaseema	0.304	0.285	0.288	0.461	0.917	0.000
Round3 Telangana	0.322	0.319	0.351	0.176	0.305	0.004
Nutritional status						
Round2 Stunted	0.408	0.399	0.428	0.337	0.359	0.254
Round2 HAZ	-1.795	-1.757	-1.869	-1.553	0.058	0.053
Household						
Round3 Urban	0.260	0.351	0.188	0.275	0.000	0.142
Round3 Household size	5.472	5.243	5.652	5.431	0.006	0.343
Round3 Wealth index	0.442	0.390	0.465	0.526	0.000	0.000
Round3 Income (thousands of rupees)	43.093	41.004	43.077	51.514	0.398	0.027
Caregiver and father						
Round2 Caregiver education	1.771	1.701	1.494	3.510	0.292	0.000
Round2 Father education	3.670	3.532	3.441	5.422	0.741	0.000
Schooling						
Attending public school	0.582	0.624	0.541	0.627	0.010	0.950
Intending to attend public school	0.418	0.376	0.459	0.373	0.070	0.970
MDMS	0.582	0.624	0.541	0.627	0.010	0.950
MDMS * Born 2001	0.500	0.526	0.470	0.549	0.091	0.675

Source: Young Lives-India. Means are for children observed in the three rounds, attending or intending to attend public schools and with the cognitive skills measure not missing (N= 1,047). LCs include the: Scheduled Caste and Scheduled Tribes. Other Backward Classes include Muslims, while UCs are those classified in the YL data as Other Castes. Child nutrition variables in Round 2 have slightly fewer than 1,047 observations.

reported).[21] Overall, we find a significant advantage among UCs in inputs and background, suggesting that these can be one source of the disparities found in cognitive and nutritional outcomes.

4 Results

4.1 The Contemporaneous Versus the Value-Added Specification

Tables A.1, A.2 and A.3 in the Appendix show complete specifications of the contemporaneous, restricted valued-added and value added regressions, respectively. They indicate that boys outperform girls; older children perform significantly better (a characteristic of the PPVT test); higher birth order children perform worse; and children in households with more members perform worse on the PPVT. Living in urban areas promotes the production of cognition. More-educated fathers and caregivers, as well as richer (or wealthier) families foster cognition. The sign and magnitude for caste dummies are as expected across specifications. These OLS regressions present initial evidence that nutritional status matters for the production of cognition. In addition, the childs gender and the caste to which a child belongs change the childs chance of having a better or worse vocabulary. For instance, the OLS specification in the first column of all the Appendix tables implies that (with no controls) being an UC child implies a higher PPVT score at age 8 compared with the base category (BC). Caste-specific effects are present regardless of the inclusion of wealth or income.

Table 2 presents results for the contemporaneous as well as the value-added regression of PPVT at age 8 on a wide range of controls at the child, household, and regional levels; and shows only the variable of interest. The table shows that, when nutritional status at age 5 is instrumented with "MDMS*Born in 2001" in column (2), the nutrition coefficient almost doubles from 12.2 percent of 1 SD

[21] In terms of inputs not considered in this paper because they either refer to Round 1 or they are from Round 2 and we do not report it because of our sample selection, there are more UC than LC households for whom the following apply: (i) Their child was born in a hospital or the birth was attended by a medically trained person, (ii) the mother took iron folate tablets/syrup during antenatal visits, (iii) the mother received a better level of antenatal care (LCs had a low-medium level of care), (iv) the child received timely immunizations, (v) the child was sent to preschool and (vi) the child attended private and NGO-run preschools, which are of higher quality.

to almost 23 percent of 1 SD; and this difference is statistically significant. The magnitude of the coefficient is very close to that of Outes-Leon et al. (2010), who exploit within-siblings variation in height-for-age measures in Peru to explore its impact on cognitive skills of 5-year-old children.[22] However, the crucial difference is that we have both the PPVT and HAZ measures taken 3 years later. The last two columns of Table 2 present the results of the value added specification. The coefficient on both PPVT and HAZ at age 5 are positive and significant. As our measure of nutrition is a proxy for the stock of nutrition until age 5 and the PPVT at age 5 includes all inputs until that age, we can conclude that late nutrition has an impact on cognitive skills. That is, nutritional status beyond the first two years of life [23] still matters, which makes the point of our study.

In Table 3 we show the first stage: "MDMS*Born in 2001" has a positive and significant effect on nutritional status at age 5 in both the contemporaneous and the value-added models, and the F-statistics are high around 70.

[22] Outes-Leon et al. estimate results using OLS models, controlling for a range of important covariates and IV techniques exploiting changes in food prices during the 2006-2008 period, as well as household shocks prior to the outcome measurement. The IV results indicate that a 1 SD increase in the height-for-age standardized measure is associated with an increase in about 0.17 to 0.21 SDs of the PPVT measure.

[23] Given that the YL data has only three measures of nutrition (at age 1, 5 and 8) we cannot really disentangle the 1,000 days effect empirically. However, our timing assumptions in which we have three-years lag between the surveys makes possible the identification of the nutrition effect from age 2 to age 5. That is, the nutrition effect from birth to age 2 will be already captured by our PPVT at age 5 measure.

Table 2: Production function of cognition

	Contemporaneous		Value Added	
PPVT age 8	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
HAZ at age 5	0.1222***	0.2273***	0.0965***	0.1144***
	(0.006)	(0.017)	(0.006)	(0.013)
PPVT at age 5			0.2125***	0.2096***
			(0.009)	(0.010)
Caregiver's education level	0.0384***	0.0387***	0.0314***	0.0315***
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-2.6935***	-2.4631***	-2.3274***	-2.2938***
	(0.221)	(0.267)	(0.169)	(0.170)
Child controls	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes	Yes
Social programs	Yes	Yes	Yes	Yes
Observations	1,031	1,031	1,031	1,031
R^2	0.228	0.217	0.261	0.260

Robust standard errors are listed in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Notes: See Tables A.1 and A.3 in the Appendix for complete results. Results that include income instead of wealth show no change in the main coefficients.

Table 3: First-stage regressions: HAZ at age 5 as dependent variable

	Contemporaneous	Value-added
	(1)	(2)
MDMS*Born in 2001	0.4686***	0.4364***
	(0.0759)	(0.0746)
PPVT at age 5		0.1275***
		(0.0347)
Observations	1031	1031
F-statistic	71.47	68.81

Robust standard errors are listed in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.2 shows results for a restricted value added. Perfect persistence is rejected and the intuition behind this important result is that, it is possible that, children who had recovered from early-life stunting by age 5 had better outcomes than those with persistent stunting. In magnitudes, a change of 1 SD in the HAZ from age 1 to age 5 will change the child's rank by 2 positions. [24]

Several of our findings are worth noting. First, the estimates reject perfect persistence, as the coefficient on lagged PPVT is statistically different from one across all specifications. Also, the persistence is low; only one-fifth of PPVT scores persist between ages 5 and 8. Still, past test scores are an important determinant of current test scores, which supports the self-productivity effects present in Cunha and Heckman (2008).[25]

Second, the valued-added (OLS) coefficient on past nutritional status is statistically different and smaller from the contemporaneous (OLS) coefficient. We expected this result because in a contemporaneous specification past nutrition might well have been capturing an unobservable characteristic such as parental motivation.

Third, when nutritional status at age 5 is instrumented with "MDMS*Born in 2001" in the value-added specification in Table 2, the effect increases by around 0.03 SDs (from 0.096 in column (3) to 0.114 in column (4)); this shows there was still some heterogeneity not completely captured by the lagged test score and that instrumenting was necessary. Even though the change in this coefficient is in the same direction as in the contemporaneous specification, the magnitude of the change is smaller and the value-added coefficient is significantly lower. Comparing the IV coefficient in the contemporaneous specifications (0.227) versus the IV coefficient of nutrition in the value-added (0.114) is informative: the inclusion of past PPVT is helping to ameliorate the identification of our coefficient of interest.

Lastly, the interpretation of the IV is important: The interaction of the MDMS dummy with an indicator of whether children were born in calendar

[24]Following Andrabi et al. (2011), we refer to ς, the parameter that links PPVT across periods, as persistence. The canonical restricted value-added assumes that $\varsigma = 1$ (Hanushek, 2003).

[25]Measurement error could also explain a smaller coefficient on lagged PPVT scores. We used an alternate measure of cognitive development available in the data, (cognitive development assessment), to instrument the PPVT. We found that the coefficient on lagged PPVT increases but remains statistically significant below 1.

year 2001 frees the coefficients from part of the "selection" problem. That is, the variation is coming from children exposed to the program who were born in 2001 vis a vis those born in 2002. Still, running this specification for the full sample (i.e., adding children who attend private/NGO or religious schools) yields weaker but similar results.

In brief, we find that a few months of extra feeding at the age of 5 had discernible differences in outcomes by age 8, even when all children in government schools will be exposed to MDMS for some time by age 8. These results are in line with those of Crookston et al. (2013) that using YL data find that children who by age 8 years had recovered from early-life stunting: (i) had better cognitive outcomes than those persistently stunted and (ii) were not significantly different in many cases from those who were never stunted.

4.2 Robustness Checks: Using Only Children Born around the Cutoff Date

One important criticism our estimation might have is that children born in 2001 could differ in many ways from children born in 2002 aside from the fact of longer exposure to the program. In particular, some of the children born in 2001 will be around one year older than some of the children born in 2002. This age difference might be associated with children being in different developmental stages which in turn can affect the effectiveness of the meals program.

For this reason we replicate our estimation but only for children born closer to the cutoff date – namely, children born in November and December 2001 – with those born in January and February 2002 (sample sizes are too small to consider only December against January). Because the age difference will be significantly smaller we should expect children to be at a similar developmental stage when exposed to the MDMS program. We find that, first, children born in November-February are similar to those of the full sample for all the relevant variables, except that those in the full sample perform slightly better in the PPVT in Round 2 and have slightly lower HAZ (see Table 1 vis a vis Table 4). Second, children born in November-December are similar to those born in January-February not only in our younger cohort data but also in the older cohort data (see Table 4 and results on the older cohort are available upon request). Third, the jump still exists (mean enrollment for children born in November and December 2001 is 61 percent, while it is 33 percent for children born in January and February 2002). Fourth, and more important, Table 5 shows that the coefficient of interest remains significant: the OLS coefficient is slightly smaller, but the IV coefficient is now larger at 0.14 SD.

4.3 Heterogeneous effects

This section shows the existence of heterogenous effects of nutrition on cognition. It might well be that the MDMS program had an effect on nutrition, but that it was particularly concentrated on those children suffering nutritional deficits. And indeed, Singh et al. (2013) find that the entire effect in their paper comes from rural, drought-affected children, which is consistent with the catch-up growth literature. For this reason, we replicate our estimation for the drought affected children vis a vis the not-drought affected. The results are illuminating: the size of the coefficient is four-fold (0.24SD) for those children whose families have been affected by drought in the last four years before the Round 2 survey. The latter reflects the fact that the responsiveness of cognition to nutrition at later ages might be stronger when the levels of nutrition are low at baseline.

Table 4: Means and T-tests of main variables by sample

	Born in Nov-Dec		Born Jan-Feb		T-test
	Mean	SD	mean	SD	(P-value)
	(1)	(2)	(3)	(4)	(5)
Child					
Cognitive Scores					
Round2 PPVT	31.582	22.210	33.731	24.661	0.423
Round3 PPVT	51.518	27.588	50.567	24.594	0.748
Individual characteristics					
Scheduled Caste	0.191	0.395	0.263	0.442	0.135
Scheduled Tribe	0.156	0.364	0.158	0.366	0.964
Backward Caste	0.560	0.498	0.480	0.501	0.156
Upper Caste	0.092	0.290	0.099	0.300	0.830
Nutritional status					
Round2 Stunted	0.426	0.496	0.345	0.477	0.146
Round2 HAZ	-1.779	0.859	-1.667	0.938	0.277
Round3 Stunted	0.390	0.490	0.333	0.473	0.300
Round3 HAZ	-1.718	1.067	-1.591	1.205	0.331
Household					
Round2 Urban	0.326	0.471	0.304	0.461	0.676
Round3 Urban	0.291	0.456	0.292	0.456	0.975
Round2 Household size	5.645	2.074	5.620	1.953	0.911
Round3 Household size	5.723	2.391	5.404	1.801	0.179
Round2 Wealth index	0.270	0.124	0.275	0.158	0.757
Round3 Wealth index	0.434	0.142	0.436	0.157	0.947
Round3 Income (thousands of rupees.)	44.249	42.187	39.811	36.529	0.320
Caregiver and Father					
Round2 Caregiver education	1.589	2.974	2.111	3.436	0.156
Round2 Father education	3.404	4.178	3.994	4.633	0.243
Observations	141		171		

Source: Young Lives-India. Means are for children observed in the three rounds, attending or intending to attend public schools and with the cognitive skills measure not missing (N= 1047). LCs include the: Scheduled Caste and Scheduled Tribes. Other Backward Classes include Muslims, while UCs are those classified in the YL data as Other Castes.

Table 5: Production function of cognition. Value-added equation: Children born around Cutoff date

PPVT age 8	Full Sample OLS (1)	Full Sample IV (2)	Born Nov-Feb OLS (3)	Born Nov-Feb IV (4)
HAZ at age 5	0.0965***	0.1144***	0.0689***	0.1432***
	(0.006)	(0.013)	(0.010)	(0.051)
PPVT age 5	0.2125***	0.2096***	0.1981***	0.1836***
	(0.009)	(0.010)	(0.013)	(0.005)
	(0.000)	(0.000)	(0.000)	(0.000)
Caregiver's education level	0.0314***	0.0315***	0.0435***	0.0432***
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	-2.3274***	-2.2938***	-1.0864**	-0.7051**
	(0.169)	(0.170)	(0.335)	(0.280)
Child controls	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes	Yes
Social programs	Yes	Yes	Yes	Yes
Observations	1,031	1,031	312	312
R^2	0.261	0.260	0.348	0.343

Robust standard errors are listed in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Production function of cognition: Value-added equation: Drought and Not-Drought affected children

PPVT age 8	Drought IV (1)	Not-Drought IV (2)
HAZ at age 5	0.236***	0.064***
	(0.053)	(0.019)
PPVT age 5	0.180***	0.214***
	(0.015)	(0.013)
Caregiver's education level	0.028***	0.034***
	(0.001)	(0.003)
Constant	-1.488***	-2.611***
	(0.565)	(0.270)
Child controls	Yes	Yes
Household controls	Yes	Yes
Village fixed e.ect	Yes	Yes
Social programs	Yes	Yes
Observations	362	669
R^2	0.250	0.290

Robust standard errors are listed in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.4 Caste Test Score Gaps

It is not clear whether the estimate of our coefficient of interest (that ranges from 11 to 14 percent of 1SD) is small or big. Impact evaluation estimates of nutritional or early childhood programs range from 0.20-0.30 of 1 SD (Nores and Barnett, 2010). Previous literature on the exact same question, and using the same data but 4 years earlier for both outcomes of interest find a coefficient of around 0.20-0.37 of 1 SD (Sanchez, 2009 and Outes et al., 2010). Crookston et al (2011) find a correlation of HAZ at around age 1 and PPVT at age 8 of 0.04-0.11. Moreover, they find that unpredicted changes in HAZ between ages 1 and 8 was positively associated with PPVT (effect range from 0.02-0.10). Our figures are similar to the upper-range of Crookston and co-authors. Still, in order to put in context the magnitude of our coefficient of interest, we use the production function estimates from our preferred IV specification in column (4) in Table 2, and examine in Table 7 the extent to which differences in HAZ can account for caste disparities in test scores.

The estimated production function coefficients do vary by caste and gender; therefore, the gap in the predicted test scores will arise from both "pure" caste effects (by gender) and by caste differences in various inputs. Therefore, in column (2) we examine how the predicted test score gaps vary if we compensate LC children with low HAZ with the average level of HAZ for UC children (i.e., we assign the average HAZ of an UC boy to each LC boy with a HAZ below the average HAZ of an UC boy and do the same with girls). Table 7 shows that if HAZ is equalized in this way, then the PPVT score gap would be reduced by 26 percent (or 5.5 percent of 1 SD). The relative gap is closed by more than double for girls (46.3 percent vs. 20.5 percent) because their caste-gap is much smaller in absolute terms. Another interesting point is to note the amount of units of nutrition we assign individually; we give more to girls in our simulation because many LC girls perform much worse than the average UC girl.

The simulations in column (3) show that a smaller (almost half) absolute gap would be closed by leveling family school expenditures (0.03), but this represents an average reduction of 12.45 percent and 23 percent for boys and girls, respectively. Given the potential endogeneity of expenditure, we need to be very cautious in interpreting this last column, which is provided only for

Table 7: PPVT caste gap closed by nutrition and school expenditures: IV Value-Added specification

	Actual caste gap	Closed by nutrition	Closed by school expenditures
	(1)	(2)	(3)
All	0.211	0.055	0.03
		(26.0%)	14.37%
Boys	0.272	0.056	0.033
		(20.5%)	12.45%
Girls	0.116	0.054	0.027
		(46.3%)	22.95%

Note 1: The percentage of the gap closed is listed in parentheses.

comparison purposes.

These simulations show that while the caste gap for boys is more than double that of girls, the amount in units of nutrition needed to compensate girls is larger. The latter seems an indication of pro-male discrimination. This finding is consistent with those of some recent papers on India of differential treatment of girls and boys: Rose (2000) and Barcellos et al. (2012), for example, demonstrate differences in time allocation of mothers in Indian households with and without sons. Jayachandran and Kuziemko (2012) identify gender differences in the duration of breastfeeding of young children. In general, however, the literature on gender bias in intra-household allocation often does not find evidence of differential treatment of children. The fact that UC families seem to discriminate more against their daughters (the gender gap in the PPVT at age 8 is 41 percent of 1 SD for UC but only 13 percent of 1 SD for the LC) is a new finding in this extensive literature that should be further explored.

Moreover, it is interesting to note that our results are also partly consistent with those of Sachar (2006), who finds that once children are placed in "more favourable" circumstances (i.e., when parents, especially mothers, are literate and when infrastructure facilities are better), intercommunity (Hindus/SC-ST/Muslims) differences in enrollment rates become insignificant (Sachar 2006). In our case, the gaps after the counterfactual exercise still exist, although to a lesser extent.

5 Conclusions and Further Research

We explore the (late) nutrition-cognition link using novel panel data from India for very young children. The survey allows us to estimate a value-added model of cognitive development that corrects for biases in the previous literature. Moreover, we use exposure to the national Mid Day Meal Scheme interacted with a nonlinearity in how birth year exogenously affects the probability of enrollment in public schools as an instrumental variable. We find that a 1 SD increase in height-for-age at 5 years of age (i.e beyond the 1,000 days window of opportunity) leads to cognitive test scores 11 to 14 percent of a standard deviation higher at age 8. Although seemingly small, this positive and significant effect supports the recent strand of literature on catch-up growth as we do find bigger effects for drought-affected children. Our analysis also suggests that compensating low-caste children with the average nutritional status of their upper-caste counterparts would close around one-fourth of the existing caste cognitive differentials for boys; while for girls, the gap is closed by half.

A policy implication of our study is that when decisions are made about where to invest scarce development resources, nutrition seems an important factor. Moreover, it seems that the assumption that the window of opportunity for effective intervention closes after 2 years of age is somehow contested by our results. Despite that early interventions remain critical, interventions to improve the nutrition of preprimary and early primary school–age children also merit consideration.

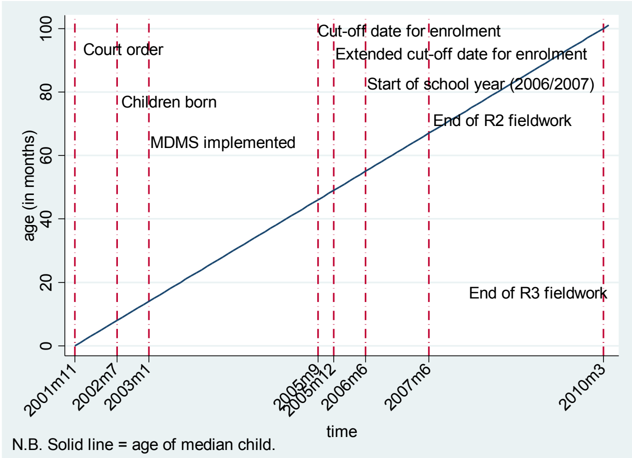
One caveat should be considered in this paper. We have a selected sample of children in public schools or intending to attend public schools. Despite the fact that the main results do not change when we include children attending private, NGO, or religious schools, the caste gap becomes almost double in the full sample. This is because it seems we are losing rich UC children with high vocabularies.

Future research might consider an analysis of children in the older cohort (8- to 16-year-olds) to extrapolate our results to older ages and other cognitive tests.

1.5

Appendix 1: Figures and Tables

Figure A.1: Timeline of relevant events by age of child



Source: Authors calculations based on YL data.

Table A.1: Production function of cognition: contemporanous equation

PPVT age 8	(1) OLS	(2) OLS	(3) IV
HAZ at age 5		0.1222***	0.2273***
		(0.007)	(0.017)
Scheduled caste	0.1462***	0.1436***	0.1269***
	(0.014)	(0.024)	(0.024)
Scheduled tribe	-0.0315	-0.1673***	-0.1734***
	(0.024)	(0.031)	(0.050)
Upper castes	0.2583***	-0.0440	-0.0611
	(0.024)	(0.046)	(0.047)
Scheduled caste* Male dummy		-0.1423**	-0.1465***
		(0.056)	(0.056)
Scheduled tribe* Male dummy		0.2378***	0.2334***
		(0.042)	(0.039)
Upper castes* Male dummy		0.0005	-0.0114
		(0.062)	(0.063)
Male dummy		0.1836***	0.1990***
		(0.018)	(0.017)
Age of child (months)		0.0273***	0.0279***
		(0.002)	(0.002)
First born dummy		-1.1002***	-1.0280***
		(0.035)	(0.026)
Last born dummy		-0.1170***	-0.1175***
		(0.008)	(0.007)
Urban dummy		0.2034***	0.2177***
		(0.019)	(0.019)
Household size		-0.0220***	-0.0217***
		(0.002)	(0.002)
Caregiver's education level		0.0384***	0.0387***
		(0.002)	(0.002)
Constant	0.3001***	-2.6935***	-2.4631***
	(0.014)	(0.223)	(0.264)
Observations	1,031	1,031	1,031
R^2	0.038	0.228	0.217

Robust standard errors are listed in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.2: Production function of cognition: restricted value-added equation

PPVT age 8	(1) OLS	(2) OLS	(3) IV
HAZ at age 5		0.0042	0.0010
		(0.008)	(0.008)
Change in HAZ			0.0178***
			(0.004)
Scheduled caste	0.1196***	0.2019***	0.2015***
	(0.026)	(0.061)	(0.061)
Scheduled tribe	-0.6801***	-0.4833***	-0.4851***
	(0.036)	(0.103)	(0.103)
Upper castes	0.1476***	0.0254	0.0277
	(0.027)	(0.069)	(0.070)
Scheduled caste* Male dummy		-0.2514***	-0.2546***
		(0.084)	(0.084)
Scheduled tribe* Male dummy		0.0693	0.0670
		(0.066)	(0.066)
Upper castes* Male dummy		0.0372	0.0369
		(0.087)	(0.088)
Male dummy		0.2081***	0.2096***
		(0.022)	(0.022)
Age of child (months)		0.0064***	0.0052***
		(0.001)	(0.001)
First born dummy		-2.6024***	-2.5907***
		(0.045)	(0.044)
Last born dummy		-0.0964***	-0.0953***
		(0.008)	(0.008)
Urban dummy		-0.1625**	-0.1626**
		(0.066)	(0.066)
Household size		-0.0077**	-0.0075**
		(0.003)	(0.003)
Caregiver's education level		0.0055*	0.0057*
		(0.003)	(0.003)
Constant	-0.5721***	-0.9438***	-0.8231***
	(0.016)	(0.175)	(0.180)
Observations	1,031	1,031	1,031
R^2	0.088	0.161	0.161

Robust standard errors are listed in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Production function of cognition: value-added equation

PPVT age 8	(1) OLS	(2) OLS	(3) IV
HAZ at age 5		0.0997***	0.1149***
		(0.006)	(0.013)
Lag PPVT	0.2997***	0.2084***	0.2059***
	(0.009)	(0.010)	(0.010)
Scheduled caste	0.1382***	0.1558***	0.1531***
	(0.011)	(0.029)	(0.028)
Scheduled tribe	-0.2259***	-0.2332***	-0.2333***
	(0.023)	(0.059)	(0.056)
Upper castes	0.2251***	-0.0296	-0.0323
	(0.025)	(0.051)	(0.050)
Scheduled caste* Male dummy		-0.1650**	-0.1654***
		(0.061)	(0.058)
Scheduled tribe* Male dummy		0.2027***	0.2025***
		(0.047)	(0.044)
Upper castes* Male dummy		0.0082	0.0063
		(0.067)	(0.064)
Male dummy		0.1887***	0.1910***
		(0.018)	(0.017)
Age of child (months)		0.0229***	0.0231***
		(0.002)	(0.002)
First born dummy		-1.4132***	-1.3984***
		(0.028)	(0.019)
Last born dummy		-0.1127***	-0.1128***
		(0.007)	(0.007)
Urban dummy		0.1271***	0.1302***
		(0.030)	(0.030)
Household size		-0.0190***	-0.0190***
		(0.002)	(0.002)
Caregiver's education level		0.0315***	0.0316***
		(0.002)	(0.002)
Constant	0.0387**	-2.3383***	-2.3090***
	(0.018)	(0.174)	(0.173)
Observations	1,031	1,031	1,031
R^2	0.112	0.261	0.260

Robust standard errors are listed in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Appendix 2: The caste system in Andhra Pradesh

The caste system is still extremely important in India in various spheres, not the least politically. The Other Castes (also called Upper Castes, as defined here) are the category of forward castes, who traditionally enjoy a more privileged socioeconomic status. At the other end of the spectrum, the Scheduled Castes (SCs) and Scheduled Tribes (STs) are traditionally disadvantaged communities. SCs are the lowest in the traditional caste structure. They were formerly known as the untouchables and now call themselves Dalit. In rural Andhra Pradesh, SC colonies are located separately, and in most cases, away from the main villages. These colonies are named after the caste, and even in the official records are often called harijana wada (or Dalit colonies). They have been subjected to discrimination for centuries and therefore had no access to basic services, including education. National legislation aims to prohibit untouchability and discrimination. STs are the indigenous people, living in and dependent on forests. Different groups of tribes live in different parts of Andhra Pradesh and vary in their culture, language and lifestyles. Though a good number of them are mainstreamed and live in plain areas, a considerable proportion continues to live on isolated hilltops with little access to services. Backward Classes (BCs) are people belonging to a group of castes who are considered to be backward in view of the low level of the caste in the structure. In Andhra Pradesh, the BCs are further divided into four groups (ABCD) and some caste groups are placed in each of these subgroups. Recently, the High Court has ordered the inclusion of a fifth subgroup, E, and Muslims have been placed into this category.

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