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Birth Weight and Cognitive Development during Childhood: Evidence from India

Santosh Kumar[1*], Kaushalendra Kumar[2], Ramanan Laxminarayan[3], Arindam Nandi[4]

ABSTRACT

Health at birth is an important indicator of human capital development over the life course. This paper uses longitudinal data from the Young Lives survey and employs instrumental variable regression models to estimate the effect of birth weight on cognitive development during childhood in India. We find that a 10 percent increase in birth weight increases cognitive test score by 8.1 percent or 0.11 standard deviations at ages 5-8 years. Low birth weight infants experienced a lower test score compared with normal birth weight infants. The positive effect of birth weight on a cognitive test score is larger for boys, children from rural or poor households, and those with less-educated mothers. Our findings suggest that health policies designed to improve birth weight could improve human capital in resource-poor settings.

JEL: I12, I15, I18, J13, J24, O12.

Keywords: Birth weight, Test score, Cognition, PPVT, Children, Instrumental variable, India.

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1. Introduction

Health endowment at birth, as indicated by low birth weight (LBW), is a strong predictor of a wide range of later-life health, schooling, and economic outcomes (Currie and Vogl, 2013). Recent empirical studies show that LBW infants, defined as weighing less than 2,500 grams, have worse human capital, schooling, adult health, and earnings compared with normal birth weight infants (Behrman and Rosenzweig, 2004; Figlio *et al*., 2014, Bhardwaj, Eberhard, and Nielson, 2018).[1] These findings thus imply that improving birth weight could help reduce poverty in low- and middle-income countries (LMICs).

There is considerable evidence on the effects of low birth weight on adult outcomes such as education and wages (Figlio *et al*., 2014; Bharadwaj *et al*., 2018). However, there is less evidence on the effects of birth weight on child outcomes such as cognitive ability, human capital accumulation, and how cognitive development evolves between birth and mid-childhood (5-8 years). Mid-childhood outcomes are important because the birth weight effects on adult outcomes manifest through the mid-childhood years and adult outcomes take many years to manifest. The fetal origins literature further indicates that catch-up growth of children is more likely to happen during mid-childhood compared with adulthood due to gradual scarring of brain cells. Therefore, for effective policy design, a better understanding of the developmental trajectories in the intervening period of early- and mid-childhood could be helpful (Almond, Currie, and Duque, 2018).[2] Another gap in the literature is the limited evidence on the heterogenous effects of birth weight in a low-income setting, whether the effect of birth weight on cognitive ability varies by ages or household characteristics.

In this study, we aim to fill this gap by analyzing relationship between birth weight and cognitive outcomes in mid-childhood life-cycle (5-8 years) of children. We use the Young Lives (YL) data from the southern Indian state of Andhra Pradesh, and estimate the causal effect of birth weight - an indicator of initial health endowment - on children's Peabody Picture Vocabulary Test (PPVT) score, a measure of cognitive ability.[3]

[1]Other important studies in this area include, see Oreopoulos *et al*. (2006), Black, Devereux, and Salvanes, (2007), Royer (2009), Almond and Currie (2011).
[2]Almond *et al*. (2018) termed the lack of knowledge about the growth trajectory from early to mid-childhood as "the missing middle years".
[3]The PPVT module requires respondents to select the pictures that best represent the meaning of a series of

An estimated 18% of Indian infants born during 2010-2015 were low birth weight (LBW), the second highest LBW rate in South Asia (NFHS-4). India has seen tremendous improvement in access to education and in primary school enrollment, with at least 96% enrollment since 2010. However, learning outcomes remain poor and declining in many states (ASER, 2018). Learning deficit is pervasive at the elementary level; only 42.5% of grade III children were able to read grade I text, only 32% children in grade II could read simple words in English, and slightly more than one-fourth of the grade III children could do a 2-digit subtraction in 2016 (ASER, 2016).

Studies of the predictive role of birth weight on cognitive ability are largely based on high-income countries. However, a few studies have estimated the effect of birth weight on cognitive outcomes in LMICs (Currie and Vogl, 2013; Nandi et al., 2017). The effect of initial health endowment on human capital could be qualitatively different in LMICs because poor schooling may prevent cognitive ability from translating into high levels of human capital. Furthermore, there may be gender and other biases in allocation of resources within the household which could also attenuate the link between health at birth and human capital later in life. The effect of birth weight on human capital outcomes could depend on the intra-household allocation of resources among children with differing abilities and on parental decisions to invest resources based on their birth endowment (Almond and Mazumdar, 2013).

Furthermore, recent studies have found evidence of catch-up suggesting that parental investments, preferences, and public policies could weaken the adverse effects of the fetal disadvantage in the long-run (Mani, 2012; Anand *et al*., 2018). Parents who exhibit compensatory behavior would allocate a higher fraction of resources to low birthweight children, and therefore, these LBW children might catch-up in the long-run.[4] Other parents may choose to reinforce the birth disadvantage by disproportionately allocating resources to higher birth weight children in the expectation there would be greater returns to their investment in these children. These behaviors have important implication for the role of complementarities in human capital formation (Cunha and Heckman, 2007). Whether

stimulus words read out by the examiner.

[4]The debate on nature versus nurture and the combined effect of genetic factors and early life experiences are discussed in detail in Manski (2011). Baguet and Dumas (2019) found limited evidence of catch-up between ages 8-22 years in Cebu, Philippines.

parental inputs and birth endowment are complements or substitutes can be inferred by comparing the birth weight effects on cognitive ability across households of different characteristics (Figlio et al., 2014). If the effects of birth weight on cognitive outcomes are stronger(weaker) for socially disadvantaged children than socially advantaged children, then parental inputs and birth endowment could be substitutes(complements). In this study, we analyze the complementarity between parental investments and birth endowment through estimation of heterogeneity in birth weight effects by demographic and socioeconomic characteristics of the households.

Estimating the causal effect of birth weight on cognitive development is challenged by sample selection bias, endogeneity of birth weight, and potential unobserved heterogeneity. We address the issue of endogeneity by estimating an instrumental variable (IV) model and by controlling for a large set of potential confounding factors at the child, mother, and the household level. We use a binary indicator of preterm birth (PTB) and mother's height jointly as instruments.[5] Furthermore, we examine the heterogeneity in the effects of birth weight by the child (gender and age), mother (education) and household characteristics (wealth, social group, and location). Finally, we estimate the quantile regression model to uncover the distributional impacts of birth weight on the test score.

To preview our results, we find that birth weight has a positive and statistically significant effect on the PPVT score during mid-childhood years in India. The effect is sizable and economically meaningful: a 10% increase in birth weight increases the PPVT score by 8.1% and the z-score by 0.11. LBW babies have 0.91 standard deviations lower test score compared with non-LBW babies. Examining whether the effect of birth weight on cognitive ability vary by ages, we find statistically insignificant effects at age 5 but effects become statistically significant at age 8, which is consistent with the findings in Figlio et al. (2014). Furthermore, we show that the effect of birth weight differs significantly by socioeconomic and demographic factors: rural and poor children, boys, and children of less-educated mothers are more likely to benefit from improved neonatal outcomes. The quantile regression results show that the effect of birth weight is higher and statistically significant in the bottom two terciles of the PPVT score distribution.

[5]Preterm births have gestation period of less than 37 weeks.

Our study contributes to the literature on early childhood conditions and human capital accumulation in several ways. First, to the best of our knowledge, ours is the first study to explore this topic in a causal framework in India, possibly due to the paucity of the data. Our findings contribute to the growing body of evidence on the adverse effects of low birth weight on the cognitive ability of children. It further contributes to our understanding of these linkages in resource-poor settings that witness both poor birth outcomes and low human capital formation. Second, our study uses an instrumental variable method to explicitly address endogeneity due to unobserved heterogeneity and measurement errors; this approach has not been used frequently in previous studies in this area.[6] Previous studies have addressed endogeneity in a twin-fixed effect models but these models fail to control for birth order and birth endowment effects. Third, unlike most previous studies which look at adult outcomes, we focus on mid-childhood outcomes, the channel through which the adult outcomes are manifested. In terms of policy intervention and evaluating the impacts of early-life programs, mid-childhood outcomes are preferred over adult outcomes (Almond et al., 2018). Fourth, we investigate the effects of birth weight by household characteristics and socioeconomic status, which provides insight into the interaction between parental inputs and birth outcomes. Understanding the nature of the interaction between parental investment and neonatal health is crucial for human capital formation. Fifth, in contrast to years of schooling we use PPVT, measure of cognitive ability, because cognitive skills rather than school attainment has been found to be an important determinant of labor market outcomes in high- and low-income countries (Hanushek and Woessmann, 2008). Finally, in contrast to previous studies, our study analyzes a recent cohort (born in 2000) whose developmental path is malleable and can still be influenced by targeted public policies.[7]

The remainder of the paper is structured as follows. In section 2, we briefly discuss the relevant literature. Section 3 describes the data and variables used in the analysis. Section 4 discusses the econometric analyses and empirical specifications. Section 5

[6]Two previous studies that use IV method to examine the birthweight effects include Lin, Leung, and Schooling (2017) and Lin and Liu (2009).
[7]Previous studies have mostly analyzed adults who have already completed schooling and are in labor market. For this set of samples, it might be too late to design policy to mitigate the effects of poor neonatal outcomes.

presents and discusses the empirical findings on the effect of birth weight on cognitive development. In section 6 we present the robustness of our results. We conclude and discuss the policy implications of our findings in section 7.

2. Related literature

2.1 Previous studies

The literature on the long-run adverse implications of low birth weight on cognitive outcomes is growing, however, majority of these studies are in high-income countries (Almond, Currie, Duque; 2018). In terms of methodology, the most common technique to estimate the causal impacts of birth weight on childhood and adult outcomes are twin- and sibling-fixed effects models. These models control for family background, socioeconomic status, and genetic factors. The evidence on the association between birth weight and cognition is mixed and the size of the effect depends on the empirical model, country context, grade, and age profile of the children.

Using a sample of 804 twins from Minnesota, Behrman and Rosenzweig (2004) find a positive relationship between birth weight and adult height, earnings, and schooling attainment in the US. They show that that the twin who is heavier by about 450 grams is likely to be more educated (by 0.7 years), earn 7% more and is taller by 0.6 inches at age 45 years. Black et al. (2007) confirm these findings in a Norwegian sample and find that a 10% increase in birth weight increased IQ by 0.06 points, probability of high school completion by less than 1 percentage point, and full-time earnings by about 1%. Using administrative data for children born in Florida from 1992-2002, Figlio et al. (2014) find that a 10% increase in birth weight is associated with 0.044 standard deviation increase in test scores in grades 3-8 (9-14 years old children). The birthweight effects appear by age nine and remain constant until age 14, and surprisingly do not vary by school quality or family characteristics. Another recent study that uses data on children born between 1992 and 2002 in Chile found that a 10% increase in birth weight increases math test score by 0.02-0.04 standard deviations in grades 1-8 (6-18 years old children) (Bharadwaj et al., 2018).

Using Panel Study of Income Dynamics (PSID) from the USA, Chatterji et al. (2014) found that a 10% increase in birth weight is associated with a 0.04 standard deviation increase in math scores and the birthweight effects are mostly concentrated among infants who were born as low birth weight. A similar study conducted in Canada by Oreopoulos et al. (2008) found a positive association between birth weight and years of schooling but found mixed effects of birth weight on the language test score. In a twin fixed-effects model, another study conducted in Chile among fourth graders found that a 400 gram increase in birth weight led to 15% standard deviations increase in math test score (Torche and Echevarria, 2011).[8] In Cebu (Philippines), Baguet and Dumas (2019) show that an increase of 100 g in birthweight is associated with an increase of 0.019 standard deviation in the highest grade completed or 0.32 years of schooling at age 8 and found limited evidence of catch-up in adult years.

Most of these studies have used twin- or sibling fixed-effects model to control for common time-invariant household characteristics and look at developed countries. However, these strategies fail to control for birth order effects and differential endowments of twins (Almond and Currie, 2011). On average, twins are mostly premature and LBW babies and therefore, twin method results cannot be generalized to singletons. The instrumental variable method could deal with these concerns of unobserved heterogeneity in a better way. Two studies based on IV method found mixed evidence (Lin and Liu, 2009; Lin, Leung, and Schooling, 2017). Lin and Liu (2009) use the public health budget and the number of doctors as instrumental variables and found the effect of birth weight on grades only for the less educated and young mothers in Taiwan. In another Taiwanese study, Xie et al. (2017) show positive and significant impacts on medium- and long-term schooling outcomes. Whereas Lin et al. (2017) use genetic variants (single nucleotide polymorphisms) and twin status as instruments and found no association between

[8]Studies have also explored whether the effect of birth weight on education or IQ varies by the gestational weeks as preterm babies may have higher risks for cognitive problems. However, birth weight has not been found to be associated with IQ in China among preterm births, while birth weight was associated with IQ among 4-7 years old full-term children in China; 1 unit increase in Z-score of birth weight (450 g) was associated with an increase of 1.60 points in IQ (Huang et al., 2013). Similarly, the risk of preterm births and test score were not associated in the PSID sample in the USA (Chatterji et al., 2014).

birthweight and academic attainment in adolescence among Chinese children in Hong Kong. In Japan, Nakamuro et al. (2013) find positive impacts of birth weight on academic performance at age 15.

In summary, it turns out that in addition to high-income countries especially the USA and the Nordic countries; the effects of birth weight have been examined in a few Asian countries such as China, Hong Kong, Japan, and Taiwan as well. But these Asian countries are high-income countries and share health and educational infrastructures similar to developed countries. The effects of birth weight could be drastically different in a setting that lacks resources, unable to provide quality health and educational infrastructures, and has disparate socioeconomic and social group composition. Although the biological effects of birth weight on cognitive outcomes may be constant across countries, country-specific factors could intensify or weaken the effects of birth weight (Royer, 2009). It is, hence, important to extend this literature to other unexplored settings where low birth weight is a significant public health challenge. To the best of our knowledge, no prior study has ever attempted to investigate the causal effect of birth weight on test score particularly in the mid-childhood phase of the life cycle in India.

2.2 Birth weight and cognitive development

There are two hypotheses to explain the significant association between low birth weight and adult outcomes. The foremost explanation is based on “Fetal Origins Hypothesis or Barker’s Hypothesis” that established a strong association between poor health at birth and onset of chronic disease in adulthood (Barker, 1992). According to Barker’s hypothesis, adult outcomes are adversely impacted through health channel. Low birth weight babies are more likely to have poor childhood and adult health and therefore have adverse consequences on adult productivity and labor market outcomes. An additional channel hinges on medical evidence that low birth weight is associated with improper development of the brain, which might affect the cognitive outcomes later in life. The poor learning outcomes for the low birth weight babies might be due to impaired and restricted growth or damage of brain cells (Hack et al., 1995; Abernethy, Palaniappan, and Cooke, 2002). The development of certain brain structures, such as caudate nuclei and the hippocampus are adversely affected by low birth weight (Abernethy et al., 2002). LBW have detrimental effects on neuro-developmental outcomes (Fattal-Valevski et al., 1999; Leitner et al., 2007) as well as psychomotor performance (Villar et al., 1984; Fernald and Grantham-McGregor, 1998). This mechanism implies that the effect of low birth weight should appear before the onset of adult chronic conditions (Chatterji et al., 2014).

3. Data

3.1 Young lives survey

We use data from the Indian Young Lives (YL) survey, a longitudinal sample of children born in 1994-95 (older cohort) and 2001-02 (younger cohort). The YL study is designed to investigate the changing nature of childhood poverty and its consequences on adult outcomes in four LMICs – Ethiopia, India, Peru, and Vietnam – over a 15-year period. In each country, the cohort comprises about 2000 children aged between 6 and 18 months (younger cohort) and up to 1000 children aged between 7 and 8 years (older cohort), recruited in 2002 and sampled from 20 sentinel sites (Barnett et al, 2013). The YL data covers nutrition, health and well-being, cognitive and physical development, health behaviors and education, as well as the social, demographic, and economic status of the household. To measure cognitive achievements, the PPVT score, the Cognitive Development Assessment-Quantity test, and several other age-appropriate tests were administered to the sampled children.

The Indian YL survey sampled 2,011 six-eighteen month old children and 1,008 eight year olds. The sample is selected from 20 sentinel sites spread across three agro-climatic zones (Coastal Andhra Pradesh, Rayalaseema, and Telangana) in the southern state of Andhra Pradesh. Our analysis uses the sample of the younger cohort from the first three rounds of YL survey: the baseline round in 2002 and two follow-ups in 2006 and 2009, when the average ages of the cohort were 1, 5, and 8 years respectively. The attrition rate between baseline and follow up rounds was less than 3% for the younger cohort. Of the 2,011 younger cohort children, birth weight information was available for 868 children in 2002. We discuss issues related to sample attrition in subsection 4.4.

3.2. Variables

The PPVT score, a measure of cognitive development, is our main outcome of interest. The PPVT is a test of receptive vocabulary that is widely used to measure vocabulary reception among 30 months and older individuals (Dunn and Dunn, 1997). The PPVT was administered to the younger YL cohort at age 5 and 8 years. We use the log of PPVT score and standardized PPVT score (PPVT z-score) as the outcome variables.

The primary explanatory variable is the log of birth weight, log(BW) from the 2002 survey. Previous studies have used birth weight, log(BW), fetal growth, and an indicator of low birth weight (< 2500 grams) as explanatory variables; however, log(BW) is preferred by researchers as it accounts for nonlinearity in the effect of birth weight (Black, Devereux, and Salvanes, 2007; Chatterji et al., 2014; Figlio et al., 2014).

We control for confounding variables at the child, household, and community levels, which could affect the association between birth weight and PPVT score, drawn from the 2002 survey. The child-level variables are age, gender, and birth order of the child. Evidence suggests that later-born children attain more years of schooling in India (Kumar, 2016). Household variables that could affect the test score, including mother and father's education (whether completed primary), household social group (whether Scheduled caste and Scheduled tribe (SCST)) and religion (whether Hindu), household wealth (wealth terciles), rural residence, and length of exclusive breastfeeding are also included in the model. Breastfeeding duration has been found be positively associated with education and cognitive development in Andhra Pradesh (Nandi et al., 2017) and elsewhere (Anderson et al., 1999). The wealth index is a simple average of three indices: housing quality, access to services, and ownership of consumer durables. The average produces a value between 0 and 1, where a higher wealth index indicates a higher socio-economic status (Briones, 2017).

The analysis includes sentinel dummies to control for time-invariant characteristics such as overall development (visible and invisible infrastructures) of the sentinels/clusters. All explanatory and confounding variables are from round 1 in 2002 when children were, on average, one year old while the outcome variable, the PPVT score, is from round 2 and 3 when the average of the children was 5 and 8 years old, respectively. The 2002 survey also collected data on maternal height in centimeters and information on whether the birth was premature, which we discuss in the next section. The number of gestational weeks were reported only for children born prematurely. Due to missing information on gestational weeks for full-term babies, we are unable to control for weeks of gestation in our regression models.

4. Econometric analyses

4.1 Ordinary Least Square approach

The effect of birth weight (BW) on cognitive outcomes can be analyzed in an Ordinary Least Square (OLS) framework in the following way:

$$Y_{ijs} = \beta_0 + \beta_1 BW_{ijs} + \beta_2 C_{ijs} + \beta_3 H_{js} + \theta_s + \mu_{ijs} \tag{1}$$

where each observation is for individual child i in household j in sentinel s. Sentinel s is defined as a cluster of villages. The dependent variable Y_{ijs} denotes the log of PPVT score or PPVT z-score (standardized). BW_{ijs} is either expressed as log of birth weight or a binary indicator of low birth weight. C_{ijs} denotes child characteristics, H_{js} denotes household characteristics, θ_s is sentinel fixed-effects, and μ_{ijs} are the idiosyncratic error terms.

A direct estimation of equation (1) is subject to potential bias because unobserved determinants of the cognitive outcomes could be correlated with birth weight. Unobserved heterogeneity originating from genetic or environmental factors could potentially affect both birth weight and cognitive ability. For example, if more educated parents adopt healthy behaviors that could have a positive impact on birth weight and children's education, the OLS estimator β_1 in equation (1) will overestimate the true causal impact of birth weight on the outcomes. Most of the causal studies on the birthweight effects have either used twins or siblings fixed effect models to address the issue of omitted variable bias (Figlio et al., 2014; Bharadwaj et al., 2018). Previous studies have also used natural shocks to identify exogenous variation in birth weight (Almond and Currie, 2011). We are unable to exploit within family variation or twins because the YL data has information on only one child per household. Instead, we use an instrumental variable method and control for a wide range of confounding factors.

4.2. Instrumental variable approach

To estimate the causal effect of birth weight on cognitive outcomes, we estimate two-stage least square (2SLS) models in the instrumental variable framework. The first and second-stage regressions are of the following form:

First stage:

$$BW_{ijs} = \alpha_0 + \alpha_1 Z_{ijs} + \alpha_2 C_{ijs} + \alpha_3 H_{js} + \theta_s + \eta_{ijk} \quad (2)$$

Second stage:

$$Y_{ijs} = \beta_4 + \beta_5 \widehat{BW_{ijs}} + \beta_6 C_{ijs} + \beta_7 H_{js} + \theta_s + \epsilon_{ijs} \quad (3)$$

where each observation is for individual child i in household j in sentinel s. Sentinel s is defined as a cluster of villages. The dependent variable Y_{ijs} denotes the log of PPVT score or PPVT z-score (standardized). Z_{ijs} denotes the instruments and birth weight (BW_{ijs}) is the endogenous variable expressed as the log-transformed birth weight measured in grams. C_{ijs} denotes child characteristics (age, gender, and birth order), H_{js} denotes household characteristics (father and mother's education, social group, religion, wealth, rural, and breastfeeding), θ_s represents sentinel fixed-effects, and η_{ijk} and ϵ_{ijs} are the idiosyncratic error terms assumed independent of all other variables in equation (2) and (3). Sentinel fixed effects θ_s is included to control for time-invariant characteristics of the sentinels. Standard errors are clustered at the community level. The parameter of interest is the second-stage parameter β_5, which captures the effect of birth weight on the test score.

In the first stage, the endogenous variable BW is regressed on the instruments and the exogenous variables and in the second stage, the outcome variables (Y) is regressed on the predicted value of birth weight ($\widehat{BW_{ijs}}$) from the first stage and the exogenous variables. The instrumental variables (Z) used in this study are the *mother's height* and a binary indicator of *preterm birth* (PTB). The IV model is over-identified as we use two instruments for one endogenous regressor. The parameter β_5 is identified if the instruments satisfy the following three conditions: (i) the instruments should be correlated with the endogenous variable (relevance condition) (ii) the instruments should be correlated with the cognitive outcomes only through birth weight (exclusion condition), and (iii) instruments are more or less randomly assigned (independence). In other words, the instruments should be associated with the endogenous variable (BW), but should not be associated with any confounder of the birthweight-outcome association, nor is there any causal pathway from the instrumental variable to the outcome other than via the BW.

4.3. Instrument validity

The rationale for using the mother's height and PTB jointly as instruments for birth weight is that they are likely to affect the intrauterine environment of mothers and fetus growth. In-utero exposure to health shocks such as maternal stress, terrorist attack, and deficient maternal nutrition could affect birth weight by affecting the gestational length or intrauterine growth (Camacho, 2008; Bozzoli and Quintana-Domeque, 2014; Amarante et al., 2016). Maternal stress causes low birth weight through the premature delivery of the babies. Preterm birth (born before 37 weeks of pregnancy) is a leading cause of low birth weight and it indirectly affects neonatal mortality (WHO, 2018), which guide its choice as an instrumental variable in our study.

Mother's height is the second instrument used in our study. Mother's height and pregnancy outcomes are likely to be correlated because maternal height affects the physical environment of the uterus (shorter women may have smaller uterus size) and may reflect mother's cumulative social and nutritional conditioning that may impact the intrauterine environment and birth outcomes (Ozaltin, Hill, Subramanian, 2010; Zhang et al., 2015). Thus, maternal height and birth outcomes, including birth weight are likely to be positively correlated.

The first condition of instrument relevance can be statistically tested; however, the second condition of exclusion restriction - that the maternal height and PTB affect cognitive outcomes only through birth weight - cannot be validated empirically. The instruments could be invalid and fail the excludability criterion if the instrument affects the outcome variables though mechanism other than birth weight or there is a third factor that may affect the instrument as well as the outcome variables. Prior studies suggest that the exclusion restriction requires orthogonality between the instruments and the dependent variables conditional on all covariates and does not assume unconditional orthogonality. Therefore, it is important to control for a large set of exogenous variables in equations (2-3). We use a rich set of control variables as discussed in the data section in our IV model and believe that conditional on the inclusion of these control variables Corr (Y, Z) = 0. One way to provide suggestive evidence on the instrument's excludability is to check if the observed characteristics between preterm births and full-term births are statistically different (McClellan et al., 1994). We report the balance of observed characteristics between the preterm and the full-term in Appendix Table A1. We discuss results on the instrument's relevance and excludability condition in more detail in the results section.

However, there might be a concern that preterm birth is not completely excludable because premature birth also has direct effects on brain development, breathing disorders, and brain hemorrhage risks which are likely to affect learning ability of the preterm babies. We are unable to control for these factors, however, if these are true then our 2SLS estimates would be downward biased. Furthermore, it is possible that maternal height could affect children's cognition directly if taller mother have higher education and spend more time with children. In our estimation we include parent's education that may help eliminate any such direct effect of maternal height on the test score.

In the case of multiple instruments (an overidentified model), Wooldridge (2010) shows that the overidentification restriction can be tested by comparing NR^2_u to the critical value of $\chi^2(1)$. R^2_u is the usual R-square of 2SLS residuals (equation 3) on all of the instruments and the full set of exogenous variables. We report the results in Appendix Table A2 and discuss them in the results section.

4.4. Sample selection bias

In our study sample, birth weight is observed only for 43% of the sample. The OLS and 2SLS estimates would be biased if there are unobserved factors that are correlated with missingness of BW and also affect the cognitive outcomes or if the probability of missingness is associated with birth weight and/or with the outcomes. In case the birth weight information is missing non-randomly, it may bias the 2SLS estimates. To check if the BW information is missing randomly, we compare household characteristics of the sample with and without the BW information in Table A3. Results show that socio-demographic characteristics are different for the two samples. For many variables, the difference is statistically significant and introduces bias in our estimates of birthweight effects. To address the concern of sample selection bias, we use Heckman-type correction method (Heckman, 1979). We calculate the inverse Mills ratio from the sample selection model that predicts the likelihood of observing birth weight in the data and then include inverse mills ratio in the 2SLS model.[9]

In a robustness check, we weight the 2SLS models by inverse probability weight (IPW) to correct for non-random sample selection bias. IPW weights the complete cases by the inverse of their probability of not being missing and rebalance the sample to make it representative of the population. We observe that the BW information is missing for children who were either born at home or if their birth information was not officially documented. The BW information is missing for 81% of the home births and 31% of the health facility births. BW was recorded from government birth document for 54% of the children and for the remaining children BW information was based on the mother's recall. These two variables, availability of government birth document and home births, are the main determinants of missingness of birth weight in our study sample. Furthermore, the probability of missing data on birth weight also differs by mother's education, rural residence, and household wealth. Since these variables are included in the 2SLS models, we calculate weights by regressing a binary indicator of missingness on the probability of undocumented birth record and births at home.

4.4 Heterogeneous effects and Instrumental variable quantile regression

The average effects of birth weight estimated in equation (3) may not necessarily be uniform across different population subgroups. Household characteristics and parental preferences (compensatory or reinforcing) may modify the association between birth weight and cognitive outcomes and thus may vary by socioeconomic or sociodemographic factors. For example, parents who prefer to compensate for poor birth endowment might invest more on LBW children and hence weaken the birth weight effects on outcomes. Furthermore, examining this association by household characteristics also helps us understand the complementarity between neonatal health and parental investment (Figlio et al., 2014). To test whether parental inputs and neonatal health are complements or substitutes, we estimate equation (3) by gender of the child, parental education, the location of residence (rural vs urban), parental education, household social group, and household

[9]We predict probability of observing BW using a probit model. The probit model includes birth weight documentation, parental education, rural residence, household wealth, and home births as explanatory variables to predict BW missingness.

wealth.

Additionally, subgroup analyses to estimate heterogeneous effects is important in the IV method because of the distinction between the average treatment effect (ATE) and the local average treatment effect (LATE) (Angrist, 2004). If compliance to the instrumental variable is not homogenous, the 2SLS method essentially estimates LATE, which estimates the effect of birth weights for groups whose treatment status is manipulated by the instrument (Angrist, 2004). Since LATE is not identical across sub-groups because of the difference in the strength of the instruments across the sub-groups, the effects of birth weight might vary by household characteristics. Finally, the mean effects estimated in equation (3) may mask the birthweight effects at different quantiles of the PPVT score. For example, the marginal contribution of higher birth weight may be higher or lower at the lower quantiles compared to the higher quantiles of the PPVT distribution. The median regression is additionally estimated to complement the mean regression to analyze data with outliers. We, therefore, estimate instrumental variable quantile regression to examine whether the effects of birth weight vary by quantiles of the PPVT score.

5. Results

5.1 Descriptive summary

Table 1 shows the summary statistics of all variables used in the analysis. The average PPVT score at age 5 and age 8 is 27.44 and 58.48, respectively, indicating that the PPVT raw score has improved over time. The mean and median birth weight is 2,763.65 and 2,750 grams, respectively. About 23% of the sample is below the median birth weight. The average birth weight in rural areas (2688 grams) is 6.3% lower than the average birth weight in urban areas (2868 grams). The prevalence of low birth weight is 16.8% and 9% of the total sample were preterm births. LBW incidence is higher in rural areas (20.2%) than in urban areas (12.1%). About 80% of the preterm children were born between 32-37 weeks of gestation. Children, on average, are 64 (range: 54-76 months) and 95 (range: 86-106 months) months old in round 2 and 3, respectively, with 45% of them being female.

The average birth order is 2 and three-quarters of the children were breastfed (76%); 42% of the children were breastfed for 1-6 months, whereas 34% of the children were breastfed for 6-15 months. Mothers are less likely to be educated compared to fathers, as the primary school completion rate among mothers is 38% while it is 52% among fathers. The average mother's height is 151.4 centimeters. Households are predominantly rural (74%) and practice Hindu religion (86%). One-third of the children belong to socially disadvantaged communities (scheduled social group/scheduled tribe) and two-thirds of them belong to the bottom two wealth terciles. The wealth index in the YL survey is a weighted sum of three components: housing quality measure, consumer durables, and services. Using the wealth indices, we categorized the households into wealth terciles. Figure 1 shows the distribution of birth weight for the full sample, while figure 2 shows the birthweight distribution for rural and urban areas. There is some evidence for heaping at 2.500 and 3,000 grams in figure 1. Data in figure 2 shows that the distribution of birth weight differs by the location of residence. On average, the birth weight is lower in rural areas compared to urban areas.

5.2 First-stage of IV results

The first-stage regression shows the predictive power of our two instruments, mother's height, and pre-term births, on the birth weight of the newborns. The first stage results presented in Table 2 show that the instruments are highly correlated with BW. Mother's height and BW are positively correlated, while PTB and BW are negatively correlated. The F-statistics for mother's height is less than 10 in column 1, suggesting that the instrument is weakly correlated with BW.[10] The F-statistics for the second instrument, PTB, is greater than 10 indicating its strong relevance with BW (column 2). Thus, to improve the strength of the instruments and statistical precision of the IV estimates, we include both instruments in the 2SLS model. In an over-identified model, the use of multiple instruments increases the precision of the IV estimates compared with the separate IV estimates (Wooldridge, 2010). When we use both instruments (our preferred specification) in column 3, the F-statistics is 13.49, greater than the typical cut off of 10 for instrument relevance. These two instruments pass the weak identification tests in Column 3; the Kleibergen-Paap Wald rk F statistics is 13.49 and the Cragg-Donald Wald F statistics is 32.23. The F-test shows that the two instruments are strong, statistically significant, and robust to the inclusion of covariates and cluster fixed effects.

[10]The typical rule of thumb F-stat cut off for weak instrument is 10 (Stock and Yogo, 2005).

Although the IV condition of excludability is difficult to test statistically, we provide indirect checks in Table A1 and in the reduced-form estimates. Results in Table A1 indicate that preterm sample of children is similar to full-term sample on several socioeconomic and sociodemographic characteristics. Of the 21 variables in Table A1, the difference is statistically significant only for 6 variables, namely parent's education, gender, and birth order of the child, rural, and household wealth. However, the sign for mother's education, father's education, and wealth is negative meaning that preterm sample has more educated and wealthy parents. It is unclear in which direction the significant difference in parental characteristics will bias the 2SLS results because the direction of the bias will be determined by whether parents engage in compensatory or reinforcing behavior. None of the health behaviors variables are significantly different. The remaining variables are also similarly distributed across the two categories in Table A1.

We also test for overidentification restriction in Table 2 and Table A2. The Sargan-test p-value and Basmann p-value are always above 0.10, implying that both instruments could be included in the IV models (Table 2). Table A2 reports the results from the regression of 2SLS residuals on the instruments and the exogenous variables as suggested in Wooldridge (2010). The R-squared in Table A2 is 0.00 and NR^2_u is well below the critical value $\chi^2(1)$. This gives us confidence in the overall validity of the instruments in our IV models.

5.3 Two-stage least square results (full sample)

Table 3 reports estimates for the causal impact of birth weight on the log PPVT score. All models in Table 3 include cluster dummies and inverse mills ratio to correct for sample selection biases. Column 1 shows the reduced-form estimates, column 2 shows the OLS estimates, and columns 3-5 report 2SLS estimates. The reduced-form estimates (regression of the outcome variable on the instruments with covariates) show that mother's height and PTB are associated with the log of the PPVT score at the 10% and 5% level of significance, respectively (column 1). The OLS results that do not account for the endogeneity of BW suggest a statistically significant and positive relationship between BW and the log of the PPVT score. The OLS results imply that an increase in BW by 10% (276 grams) raises log of the PPVT score by 1.9% (column 2).[11]

Columns 3 and 4 report the results from the 2SLS models when BW is instrumented by the mother's height and preterm birth, respectively. Results in column (3) and (4) indicate that BW is positively associated with the log of the PPVT score; however, the estimates are statistically significant only in column (4). The results in column 4 indicate that a 10% increase in BW would increase the log of the PPVT score by 7.2%. Our preferred specification is the model in column (5) when BW is instrumented by both instruments - mother's height as well as preterm births. The 2SLS results in column (5) show that BW has a statistically significant causal effect on the PPVT score. The estimated 2SLS coefficient is 0.806, meaning an increase of BW by 10% will raise the log(PPVT) score by 8.1%. The 2SLS coefficient is about 5 times larger than the OLS estimate. The difference between the OLS and the 2SLS coefficients imply that the OLS model suffers from relatively large endogeneity biases and the OLS estimate is likely to underestimate the true causal impact of BW on the test score. When we include the mother's height and PTB jointly in the model in column (5), we lose a few observations due to missing information.

For ease of interpretation, the literature in education frequently uses standardized test score rather than the raw or log of the tests score as the dependent variable.[12] In Table 4, we report the effect of birth weight on standardized PPVT score (PPVT z-score). The OLS coefficient is 0.244 meaning that the standardized test score increases by 0.02 standard deviations (SD) due to an increase in BW by 10%. The 2SLS results are reported in columns (3)-(5). Results are statistically insignificant when we use mother's height as the instrument (column 3), whereas results in column (4) and (5) pass the statistical significance at 5% level of significance. With preterm birth as the instrument, the birthweight effect is 0.10 SD for a 10% increase in BW.

When we use mother's height as well as preterm births together as instruments in column 5, we find that BW has a significantly positive impact on the standardized test score. A 10% increase in BW leads to 0.11 SD increases in the PPVT z-score. These findings are robust to the addition of various child- and household-level controls, and sentinel

[11]An effective policy could affect birth weight in the range of 200-250 grams (Royer, 2009). However, the average birth weight among LBW children in our sample is 1954 grams.

[12]Z-scores capture how far the test score deviates from the mean test score of sampled children.

fixed-effects in the regression model. Compared to other studies, our results are slightly larger in magnitude. For example, a 10% increase in birth weight increased math and language test score by 0.02-0.04 SD in Chile (Bharadwaj et al., 2018); by 0.03 in Florida, USA; (Figlio et al., 2014); 400 grams increase in birth weight led to 2.6 or 5% SD increase in math scores in Chile (Torche and Echevarria, 2011). However, it should be noted that the type and design of tests may not be comparable across studies. In contrast to the studies in the USA and Chile, the PPVT test administered in India is a vocabulary and receptive test and does not include math or language component.

The WHO classifies children weighing less than 2,500 grams at birth as low birth weight and recommends designing health policies targeting LBW babies, as low birth weight is significantly associated with worse child and adult outcomes. Instead of using BW as a continuous variable, in Table 5 we estimate the impact of low birth weight (a binary indicator for having BW < 2,500 grams) on the log of the PPVT score and the standardized PPVT score. The OLS and the 2SLS results show that LBW is negatively associated with both the outcome variables. Column 2 shows that low birth weight children have 66% lower PPVT score compared to children who are not low birth weight. Per our preferred specification in column 4, LBW children have 0.91 SD lower test score compared to non-LBW children. The 2SLS coefficient is about six times larger than the OLS estimates.[13]

5.4 Two-stage least square results by age of the children

In addition to the importance of the main effects, Figlio et al. (2014) and Bharadwaj et al. (2018) emphasize the importance of trajectory and the critical period of human capital development. The ages at which the birthweight effect appears and whether the effects are persistent or not as children grow older have been addressed empirically in these two studies. Bharadwaj et al. (2018) examine the birthweight effects in grades 1-8, while Figlio et al. (2014) examine grades 3-8. In Table 6, we conduct a similar analysis by age of the

[13]The results in column 2 are slightly bigger in magnitude. Column 2 shows that low birth weight children have 66% lower PPVT score relative to non-LBW children. The standard deviation of birthweight is 547 grams in our sample, so a unit change in LBW implies a gain in birth weight of ~547 grams. Another way to interpret the results in column 2 is that an increase in BW by ~547 grams (or by 28% [547/1954]) could increase log of PPVT score by 66%. The average BW among LBW infants is 1,954 grams in our analytical sample.

children. We are unable to conduct the analyses by grades because our sample children were 5 years old in 2006 and did not start school at age 5. Therefore, no schooling data is available from round 2 of the survey. However, since we have test score data for two time periods (age 5 and age 8) we estimate our model by age instead of by grade. This analysis would be useful in knowing ages at which the effects of birth weight starts appearing. Whether they appear in early childhood or mid-childhood ages remain an important inquiry?

Bharadwaj et al. (2018) find that the effect of birth weight effect on cognition as early as age 6 whereas, in Figlio et al. (2014) study, the birthweight effect appears at age nine and in both studies the effects are stable and persistent through grade 8 (ages 14-18).[14] Our results in Table 6 show that the negative effects of poor birth outcomes do not appear by age 5 (column 1 and 3) but are statistically significant and economically meaningful at age 8. For example, a 10% increase in birth weight increases standardized test score by 0.13 standard deviations at age 8 but no significant association was estimated at age 5. Our results are somewhat similar to those of Figlio et al. (2014) and Bharadwaj et al. (2018) although the context, empirical specification, and outcomes are not always comparable. Since elementary schooling in India starts at age 5 or 6 in India, our sampled children are likely to be in grade 2 or 3 in 2009. This implies that the birth weight effect in our study starts appearing in grade 2-3 among Indian children which is consistent with the findings in Figlio et al. (2014) and Bharadwaj et al. (2018). Examining the effect of low birth weight on the test score, we find that LBW children have 1.09 SD lower test score relative to children who are not LBW (Panel B, Table 6). In summary, the poor neonatal health is not a statistically significant determinant of test score at age 5 but plays an important role in predicting the PPVT score at age 8.

5.5 Heterogeneous effects by gender, maternal education, household wealth, household caste, and location

The results show the average impacts and indicate a strong and robust causal association between birth weight and test score in the Indian YL sample. Nonetheless, the effects of birth weight on test score may vary by child and household characteristics. On the one hand, if

[14]The age-range of grade 8 students in Florida was between 14 and 18.

socioeconomic factors (income and parent's education) are substitutes with birth weight in the production of cognitive skills then the impact of birth weight on test scores will be larger for the disadvantaged groups. On the other hand, if parental behaviors and resources were complements with initial health endowment, then one would expect to see larger effects for the advantaged groups (Figlio et al., 2014). We examine the heterogeneity in the association between birth weight and test score by estimating equation (3) by gender of the child, maternal education (whether mother has completed primary schooling), household social group (SCST vs other social groups), household wealth (top tercile vs the bottom two terciles), and by location of residence (rural vs urban). Table 7 reports the heterogeneous results.

The results indicate that household socioeconomic characteristics appear to moderate the effects of birth weight on the PPVT test. Column (1) shows the results for log(PPVT) score and column 2 shows the results for standardized PPVT score. It should be noted that the *F-stat* and *N* would be identical for models in column (1) and (2) because first-stage regressions are the same for both outcomes. To save space, we only report the 2SLS results.[15] The pooled 2SLS coefficients are statistically significant for rural, boys, less educated mothers, and poor households sample. For example, the birthweight effect on the standardized PPVT score is 0.19 SD for children born to less educated mothers, whereas the association is statistically insignificant for children born to mothers who have completed primary schooling. Similarly, the relationship is larger and statistically significant (at a 10% level of significance) for children belonging to the poorer households than the richer households. The causal impact of BW on test scores also differs by gender of the child: the effect size is positive but statistically significant only for the boys and not for the girls. In contrast, neither Bharadwaj et al. (2018) nor Figlio et al. (2013) found any evidence of a differential effect of BW on test score by household characteristics. Their findings imply that some of the biological and fetal disadvantages are difficult to overcome through nurture or family resources. In contrast, our results show that "nurture" or family resources can partially remediate poor birth outcomes.

5.6 Quantile regression results

[15]The OLS results are available upon request.

We next examine whether the effect of birth weight in our study varies by the distribution of the PPVT score in a quantile regression framework. The quantile regression method is useful in estimating the effects of birth weight at different quantiles of the PPVT score distribution. The average birthweight effects showed in Table 3 and 4 may mask important causal impacts at different parts of the conditional distribution of the PPVT score. The policy response and design would be different if the effects of birth weight on test score are stronger (weaker) at higher (lower) quantiles. Figure 3 reports the estimates for the quantiles {0.20, 0.40, 0.60, 0.80}, whereas Table A5 reports the results for the several other quantiles. The dependent variables are the log of the PPVT score and the PPVT z-score. The results from instrumental variable quantile regression show that the positive effects of birth weight vary by the quantiles of the PPVT score. The estimated positive effects of birth weight on test score are statistically significant mostly at the lower and the median quantiles. An increase in birth weight raises test score throughout the range of quantiles at nearly all the quantiles below 0.6. Similarly, low birth weight has statistically significant and negative impacts on test score at quantiles below 0.6. For quantiles above 0.6, the sign of the effects is in the right direction but they are imprecisely estimated (large standard errors) and are statistically insignificant.

6. Robustness Checks

In this section, we examine the stability of our main findings in two ways. First, as a robustness check, we address sample selection bias in a different way. Instead of employing a Heckman-type correction method, we use inverse probability weighting to correct for selection bias. Columns (1) and (3) in Table 8 report the results from this analysis. The control variables in Table 8 are the same as those in Tables 3-4. Results are quite stable and similar to the main findings reported in Tables 3-4. A 10% increase in birth weight increases log(PPVT) score by 8.7% (column 1) against the benchmark estimates of 8.1% in Table 3. Similarly, the effect of a 10% increase in birth weight on standardized PPVT score is 0.12 standard deviations (column 3), which are similar to the benchmark results in Table 4.

In the case of a weak instrument and multiple instruments particularly when instruments are correlated with each other, the 2SLS estimator may exhibit bias. As a robustness check, we use jackknife instrumental variable estimator (JIVE) that is more robust to weak instrument problem as well as the correlation among multiple instruments (Angrist, 2004). Results in columns (2) and (3) in Table 8 indicate that our main findings are quite stable and robust to the estimation of an alternative version of the IV method, the JIVE approach. In fact, the JIVE results are larger in magnitude than the 2SLS estimators, confirming the positive and persistent impacts of birth weight on test scores.

In Table A6, we further show that our main results on LBW (Table 5) are robust to non-inclusion of observation, which had missing birth weight information. Although we corrected for the sample selection bias through Heckman-type correction method or inverse probability weighting, we try to bound the 2SLS estimates for LBW analysis in Table A6. Column (1) provides the benchmark coefficient from Table 5. In column (2), we assume that all observations with missing BW information are non-LBW, whereas, in column (3), they are assumed to be LBW.[16] The assumptions of all missing being either LBW or non-LBW are a bit extreme, so in column (3), we randomly assume 17% of the missing sample as LBW. The mean LBW prevalence in our analytical sample is about 17%. Assuming that all missing children are non-LBW results in a coefficient of 1.12 SD, 24% larger than the coefficient in column (1). The 2SLS point estimate is similar when we randomly assume that only 17% of the missing sample is LBW (column 4).[17]

Royer (2009) found a larger birthweight effect for infants weighing more than 2,500 grams, while no such differential effects were found in Figlio et al. (2014). Bharadwaj et al. (2018) show that being born as a low birth weight infant reduces math score by 0.1 standard deviations but they do not report their findings for infants with normal birth weight (greater or equal to 2,500 grams). To estimate these non-linear effects of birth weight, we split the sample into two groups: less than 2,500 grams and greater than or equal to 2,500 grams. The results are reported in Table A7. Results are very sensitive to heaping of birth weight at 2,500 grams and a clear picture does not emerge from this analysis. In many cases, the estimates are statistically insignificant. However, for completeness, we

[16]With these adjustments, the prevalence of LBW children changes to 7.2% and 64.3% in column 2 and 3, respectively.

[17]We cannot assume the birth weight of the missing sample; therefore, we are unable to do a similar robustness check for the log of birth weight results. Multiple imputation is an option, but we do not undertake imputation exercise in this paper.

prefer to report these results as well. Additionally, the positive effect of birth weight on the standardized PPVT score is statistically significant at 10% level of significance in the restricted sample of 1,000-3,000 grams (similar birth weight range used in Bharadwaj et al. (2018).

7. Conclusion

Despite a large body of evidence on the effect of birth weight on cognitive outcomes in developed countries, there is a dearth of comparable studies on children in LMICs. This study is among the first to examine the role of birth weight in cognitive and human capital development in a resource-poor country such as India. We address endogeneity in birth weight by adopting an instrumental variable approach. Two instruments, pre-term births and mother's height, are used to instrument birth weight in the IV model.

We find that improved birth outcomes have a positive and statistically significant impact on the PPVT score among children in the mid-childhood phase of their life cycle. An increase in birth weight by 10% results in 0.11 standard deviation increases in the PPVT score, which is economically meaningful and comparable to the effects found in the education interventions in developing countries. For examples, large-scale educational interventions (financial incentives to teachers, remedial education, and computer-assisted learning) increased test score by 0.17-0.47 standard deviations (Banerjee et al., 2007; Muralidharan and Sundararaman, 2011; Duflo, Hanna, and Ryan, 2012). The analytical model examines sampled children at two stages of their childhood, at age 5 and 8, and results show that birthweight effect is not visible at age 5 but becomes stronger and statistically significant at age 8. The heterogeneity analysis further establishes that parental inputs and neonatal outcomes are substitutes as the effect sizes are larger in magnitude for rural, boys, poor, and children born to less-educated mother. The differential effects by gender of the child, maternal education, household caste, wealth tercile, and rural residence, imply that nurture or parental investment may moderate the biological determinants of mid-childhood outcomes.

While the results presented in our study are compelling and policy-relevant, there are a few limitations. First, unlike the previous studies, we are unable to use either twin as an exogenous shock in the birth weight or household fixed-effects model due to lack of suitable data on twins or siblings. There could also be concern about the representativeness of the YL sample. Second, since the YL data oversampled poor children and was drawn from only one state of India, the data may not be representative either for the state or for the country as a whole. Third, mother's self-report of birth weight may introduce measurement error due to recall bias and this could potentially bias the estimated parameters in this study. However, previous research suggests that maternal recall data regarding birth weight can be reliable in predicting infant and childhood health in India (Subramanyam and Subramanian, 2010). Finally, we are unable to control for weeks of gestation in our model due to data limitation. Data on gestational weeks is available only for the preterm births and lack of similar information for the full-term births preclude us from including gestational weeks as an additional control in our preferred specification. In spite of these limitations, we believe that the findings from this study will engender health policy design to improve neonatal outcomes in India.

Given the economically meaningful and statistically significant association between birth weight and test score found in our study, health policies that target pregnant mothers who are at increased risk of delivering LBW babies could be an important intervention for human capital accumulation in low-resource countries. Effective public policies in this direction would require a better understanding of the social and economic determinants of poor health at birth. Future studies should explore the risk factors associated with low birth weight and subsequently examine preventive strategies that could be effective in reducing the incidence of low birth weight in developing countries. Additionally, parent's compensatory behavior and remedial education policies could reverse the adverse effects of poor neonatal conditions.

To conclude, our study contributes to the literature in several important ways. First, it is one of the handful of studies on the effect of birth weight on cognition in India. Given that LBW is disproportionately high in India, estimating its negative effects on human capital will help policymakers design interventions that can offset and compensate for the poor birth endowment. Secondly, most of the previous studies have explored adult outcomes that are mediated through mid- and late-childhood ages. In this paper, we present results on short to medium-term effects of lower birth weight and highlight the mechanism (cognition) through which adult outcomes are likely to be generated. Our understanding of the evolution of the developmental path of children at different phases of the life cycle is limited; therefore, future research should attempt to disentangle the effect of early life or neonatal conditions on mid-childhood outcomes from adult outcomes. The limited information on the "missing middle years" of childhood should be addressed in future studies so that policymakers are able to identify and design cost-effective policies for children of different ages.

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Table 1: Summary Statistics (Andhra Pradesh, India; N=1611)

	Mean	S.D.
	(1)	(2)
Outcome variables		
PPVT raw score at age 5 (2006)	27.44	21.12
PPVT raw core at age 8 (2009)	58.48	30.45
PPVT score (pooled)	43.17	30.51
PPVT z-score (pooled)	2.50	1.00
Log of raw PPVT score (pooled)	3.52	0.71
Explanatory variables		
Low birth weight	0.168	0.37
Birth weight (grams)	2763.65	547.13
Log of birth weight	7.90	0.20
Instrumental variables		
Mother's height	151.42	6.46
Preterm birth (PTB)	0.09	0.291
Child characteristics		
Age of child (in months)	95.41	3.83
Birth order	2.03	1.17
Female (%)	0.45	0.49
Exclusive breastfeeding (%)	0.76	0.42
Household characteristics		
Mother is primary schooled (%)	0.38	0.48
Father is primary schooled (%)	0.52	0.49
Rural (%)	0.74	0.43
Hindu (%)	0.86	0.33
Rich (%)	0.33	0.47
Schedule social group and scheduled tribe (%)	0.32	0.47
Sentinels (#)	20	
Districts (#)	6	
Regions (#)	3	

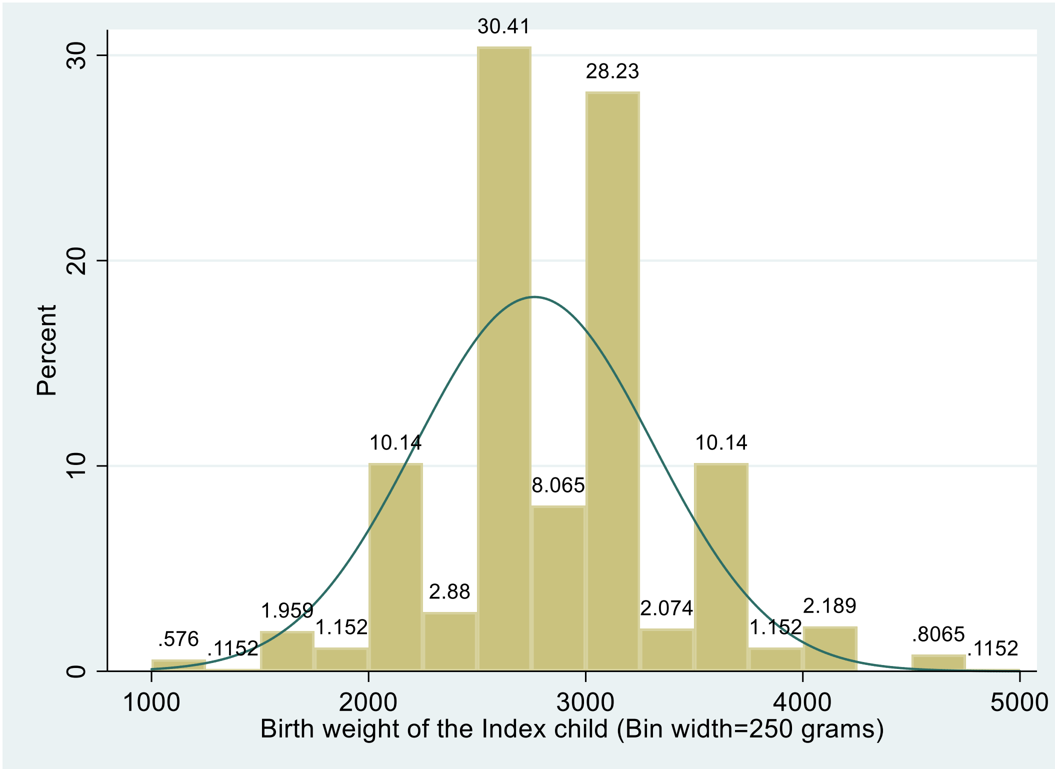


Figure 1: Distribution of birth weight

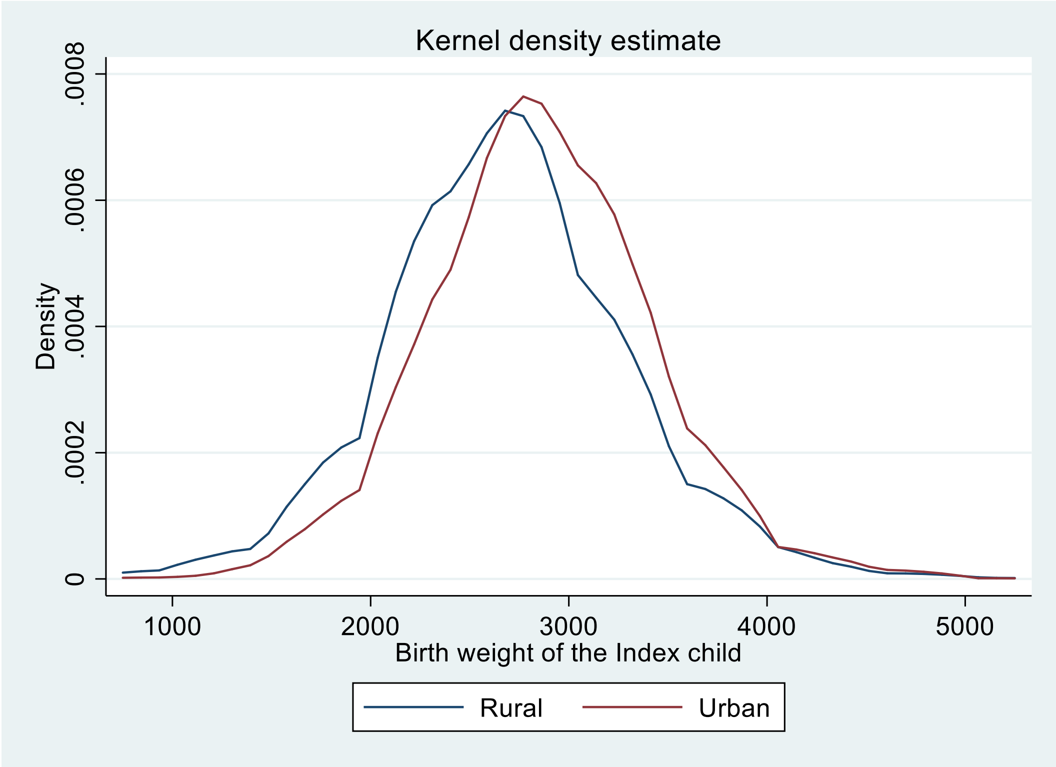


Figure 2: Kernel density distribution of birth weight for rural and urban areas

Table 2: First stage results- correlation between the instruments and the endogenous variable

	Instrument: Mother's height	Instrument: Preterm birth	Instruments: Mother's height + Preterm birth
	(1)	(2)	(3)
Mother's height	0.002**		0.002**
	(0.0008)		(0.0009)
Preterm birth		-0.123*** (0.029)	-0.122*** (0.029)
Weak identification test			
Kleibergen-Paap Wald rk F statistic	5.71	17.69	12.75
Cragg-Donald Wald F statistic	7.52	61.86	32.98
Tests of overidentifying restrictions			
Sargan test p-value			0.859
Basmann p-value			0.861
p-value for endogeneity test			0.010

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, exclusive breastfeeding, cluster dummies, and inverse mills term.
*p< 0.10, **p<0.05, ***p<0.01

Table 3: OLS and 2SLS effect of birth weight on PPVT score (log)

	Cognitive outcome: PPVT score (log)				
	Reduced-form estimates	OLS	Two Stage Least Squares		
			Instrument: Mother's height	Instrument: Preterm birth	Instruments: Mother's height + Preterm birth
	(1)	(2)	(3)	(4)	(5)
Mother's height	0.003*				
	(0.002)				
Premature delivery	-0.088**				
	(0.041)				
Birth weight (log)		0.195***	1.64	0.724*	0.806**
		(0.074)	(1.32)	(0.378)	(0.393)
Cluster fixed effects	Yes	Yes	Yes	Yes	Yes
Inverse mills ratio	No	Yes	Yes	Yes	Yes
R-squared	0.50	0.50	0.40	0.48	0.47
Observations	1521	1609	1609	1521	1521

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, and exclusive breastfeeding.
*p< 0.10, **p<0.05, ***p<0.01

Table 4: OLS and 2SLS effect of birth weight on PPVT z-score

	Cognitive outcome: PPVT z-score				
	Reduced-form estimates	OLS	Two Stage Least Squares		
			Instrument: Mother's height	Instrument: Preterm birth	Instruments: Mother's height + Preterm birth
	(1)	(2)	(3)	(4)	(5)
Mother's height	0.003				
	(0.003)				
Premature delivery	-0.126**				
	(0.059)				
Birth weight (log)		0.244**	1.61	1.04**	1.09**
		(0.123)	(1.90)	(0.504)	(0.522)
Cluster fixed effects	Yes	Yes	Yes	Yes	Yes
Inverse mills ratio	No	Yes	Yes	Yes	Yes
R-squared	0.42	0.42	0.38	0.41	0.41
Observations	1523	1609	1609	1521	1521

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, and probability of exclusive breastfeeding.
*p< 0.10, **p<0.05, ***p<0.01

Table 5: OLS and 2SLS effect of low birth weight (LBW) on PPVT z-score

	PPVT score (log)		PPVT z-score	
	OLS	2SLS	OLS	2SLS
		Instruments: Mother's height + Preterm birth		Instruments: Mother's height + Preterm birth
	(1)	(2)	(3)	(4)
Low birth weight (dummy)	-0.112***	-0.659*	-0.161	-0.906*
	(0.035)	(0.398)	(0.053)	(0.502)
Cluster fixed effects	Yes	Yes	Yes	Yes
Inverse mills ratio	Yes	Yes	Yes	Yes
R-squared	0.50	0.42	0.42	0.38
Observations	1609	1521	1609	1521

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, and probability of exclusive breastfeeding.
*p< 0.10, **p<0.05, ***p<0.01

Table 6: 2SLS effect, by child's age and grades

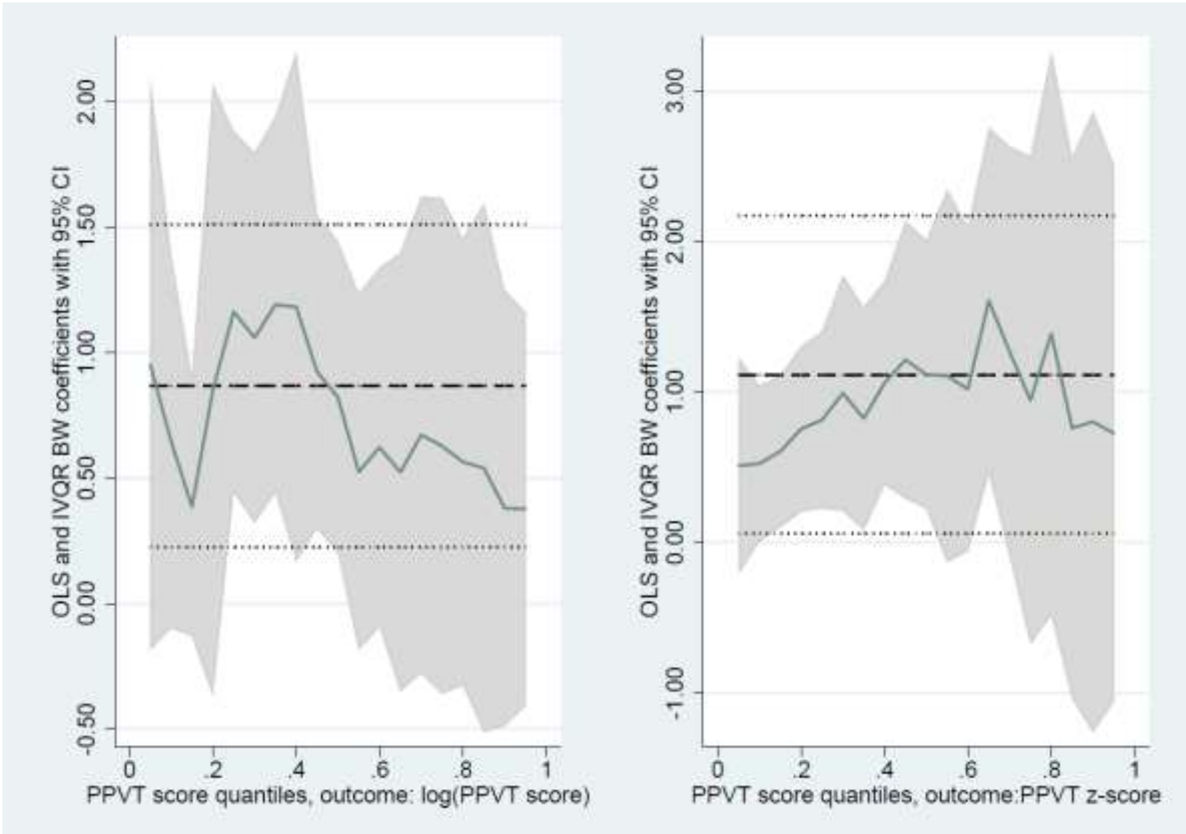
	PPVT score (log)	PPVT score (log	PPVT z-score	PPVT z-score
	Age 5	Age 8	Age 5	Age 8
	(1)	(2)	(3)	(4)
Panel A				
Birth weight (log)	1.063	0.565***	0.881	1.292**
	(0.791)	(0.219)	(1.039)	(0.571)
R-squared	0.29	0.25	0.46	0.47
Panel B				
Low birth weight (dummy)	-0.851	0.476**	-0.713	-1.099**
	(0.725)	(0.208)	(0.895)	(0.483)
R-squared	0.19	0.22	0.42	0.44
Cluster fixed effects	Yes	Yes	Yes	Yes
Inverse mills ratio	Yes	Yes	Yes	Yes
Observations	750	771	750	771

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, and probability of exclusive breastfeeding.
*p< 0.10, **p<0.05, ***p<0.01

Table 7: Heterogeneity in effects: 2SLS effects of log(BW) birth on the test scores by child, mother, and household characteristics

	PPVT score (log)	PPVT z-score	F-stat	N
	(1)	(2)	(3)	(4)
Urban	0.933	0.744	15.24	625
	(0.966)	(1.198)		
Rural	0.622**	1.149***	8.29	896
	(0.274)	(0.403)		
Boys	0.712*	1.083*	7.72	809
	(0.406)	(0.572)		
Girls	1.344*	1.617	5.99	712
	(0.714)	(1.083)		
Mother is primary schooled	0.427	0.328	7.95	877
	(0.472)	(0.662)		
Mother is not primary schooled	1.157**	1.90**	8.11	644
	(0.519)	(0.767)		
SCST	1.051	1.676	0.33	339
	(1.059)	(1.594)		
Other social group	0.576	0.857	17.84	1182
	(0.403)	(0.547)		
Poor	0.812*	1.161**	4.22	754
	(0.473)	(0.585)		
Rich	0.848	1.067	13.74	767
	(0.603)	(0.789)		

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, probability of exclusive breastfeeding, inverse mills ratio, and cluster dummies.
*p< 0.10, **p<0.05, ***p<0.01



Notes: The bold dashed lines are the OLS estimates and the light dashed lines are the 95% confidence intervals.

Figure 3: Instrumental variable quantile regression (IVQR) results

Table 8: Robustness Checks

	PPVT score (log)		PPVT z-score	
	IPW	JIVE	IPW	JIVE
	(1)	(2)	(3)	(4)
Birth weight (log)	0.869**	1.555*	1.197**	2.17*
	(0.389)	(0.807)	(0.514)	(1.236)
Cluster fixed effects	Yes	Yes	Yes	Yes
Inverse mills ratio	No	Yes	No	Yes
R-squared	0.45	0.36	0.39	0.17
Observations	1523	1521	1523	1521

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, and probability of exclusive breastfeeding. Instruments: Mother's height and Preterm birth
*p< 0.10, **p<0.05, ***p<0.01

Appendix

Table A1: Balance between preterm birth and full-term birth sample

	Preterm births (N=109)	Full-term births (N=759)	Difference (p-value)
	(1)	(2)	(1)-(2)
Child characteristics			
PPVT score (age 5)	33.5	32.2	1.35 (p=0.609)
PPVT score (age 8)	61.7	65.02	-3.3 (p=0.337)
Female child	0.31	0.48	-0.17*** (p < 0.001)
Birth order	1.65	1.84	-0.19** (p=0.05)
Child was wanted	0.95	0.92	0.03 (p=0.27)
Parent's characteristics			
Maternal age (years)	22.10	22.08	0.013 (p=0.98)
Maternal education (more than primary school)	0.71	0.57	0.15*** (p=0.004)
Maternal height	151.07	151.52	-0.46 (p=0.517)
Father education (more than primary school)	0.77	0.65	0.12** (p=0.01)
Household's characteristics			
Household size	4.95	5.18	-0.25 (p=0.27)
Household social group (SCST)	0.28	0.24	0.04 (p=0.359)
Rural	0.44	0.60	-0.16*** (p< 0.001)
Hindu religion	0.81	0.84	-0.02 (p=0.525)
Household wealth (top tercile)	0.65	0.52	0.136** (p=0.007)
Food shortage	0.05	0.03	0.02 (p=0.215)
Education expenditure (monthly)	449.3	456.7	-7.39 (p=0.479)
Health preferences and behaviors			
Exclusive breastfeeding	0.81	0.77	0.04 (p=0.392)
Antenatal care	0.78	0.77	0.01 (p=0.904)
Skilled birth attendant	0.92	0.86	0.06 (p=0.101)
Took two or more tetanus shot during pregnancy	0.85	0.86	-0.005 (p=0.90)
Took iron tablet during ANC visit	0.83	0.84	-0.01 (p=0.80)
Took folic syrup in last 3 months	0.75	0.79	-0.04 (p=0.418)

Source: The Young Lives Study. All variables are from 2002 except educational expenditure (2009). Means and proportions are reported.
*p< 0.10, **p<0.05, ***p<0.01

Table A2: Test for overidentifying restrictions

	Dependent variable: Estimated residuals from the second-stage equation	
	Coefficient	Robust standard error
	(1)	(2)
Preterm birth	0.004	0.061
Mother's height	0.0005	0.004
Age	0.000	0.004
Female	0.0001	0.042
Birth order	0.000	0.0221
Maternal education	-0.0003	0.0305
Father's education	-0.0008	0.0544
Rural	0.0004	0.1007
Scheduled social group and	0.0008	0.0379
Hindu religion	0.0006	0.058
Household wealth	0.00007	0.059
Exclusive breastfeeding	-0.0003	0.044
Cluster fixed effects	Yes	
Inverse mills ratio	Yes	
R-squared	0.0000	
Observations	1521	

Notes: OLS coefficients and the robust standard errors, clustered at the community level, are reported in columns 1 and 2, respectively.
*p< 0.10, **p<0.05, ***p<0.01

Table A3: Balance between sample with and without BW information

	BW available (N=868)	Missing BW (N=1143)	Difference (p-value)
	(1)	(2)	(1)-(2)
Child characteristics			
Female child	0.46	0.46	0.00 (p = 0.827)
Birth order	1.81	2.16	-0.36*** (p < 0.001)
Child was wanted	0.93	0.88	0.05*** (p < 0.001)
Home birth	0.22	0.71	-0.49*** (p < 0.001)
Birth document	0.54	0.02	0.52*** (p < 0.001)
Parent's characteristics			
Maternal age (years)	22.01	22.34	-0.252 (p = 0.195)
Maternal education (more than primary school)	0.59	0.25	0.34*** (p < 0.001)
Maternal height	151.47	151.40	0.065 (p = 0.826)
Father education (more than primary school)	0.67	0.40	0.27*** (p < 0.001)
Household's characteristics			
Household size	5.15	5.62	-0.47*** (p < 0.001)
Household social group (SCST)	0.249	0.391	-0.14*** (p < 0.001)
Rural			
Hindu religion	0.58	0.88	-0.30*** (p < 0.001)
Household wealth (top tercile)	0.53	0.18	0.35*** (p < 0.001)
Food shortage	0.03	0.07	-0.04*** (p < 0.001)
Education expenditure (monthly)	455.8	477.2	-21.4*** (p < 0.001)
Health preferences and behaviors			
Exclusive breastfeeding	0.775	0.746	0.03 (p = 0.131)
Antenatal care			
Skilled birth attendant	0.87	0.49	0.38*** (p < 0.001)
Took two or more tetanus shot during pregnancy	0.6	0.84	0.02 (p = 0.337)
Took iron tablet during antenatal visit	0.83	0.81	0.02 (p = 0.254)
Took folic syrup in last 3 months	0.78	0.75	0.03* ((p = 0.06)

Source: The Young Lives Study. All variables are from 2002 except educational expenditure (2009). Means and proportions are reported.
*p< 0.10, **p<0.05, ***p<0.01

Table A4: 2SLS effect, by grades

	PPVT z-score	PPVT z-score	PPVT z-score	PPVT z-score
	Grade 0	Grade 1	Grade 2	Grade 3
	(1)	(2)	(3)	(4)
Birth weight (log)	-0.072	1.78	1.87**	-0.175
	(1.09)	(1.19)	(0.809)	(1.26)
F-stat	1.39	3.14	30.96	1.57
Cluster fixed effects	Yes	Yes	Yes	Yes
Inverse mills ratio	Yes	Yes	Yes	Yes
R-squared	0.30	0.42	0.52	0.47
Observations	126	187	363	127

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, and probability of exclusive breastfeeding.
*p< 0.10, **p<0.05, ***p<0.01

Table A5: Instrumental variable quantile regression results

	Quantiles											2SLS
	0.1	0.2	0.25	0.3	0.4	0.5	0.6	0.7	0.75	0.8	0.9	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PPVT score (log)												
Birth weight (log)	0.65	0.85***	1.16***	1.06***	1.18***	0.82**	0.62	0.67	0.63	0.57*	0.38	0.851**
	(0.49)	(0.25)	(0.34)	(0.30)	(0.34)	(0.37)	(0.38)	(0.47)	(0.46)	(0.33)	(0.30)	(0.404)
Low birth weight	-0.54	-0.72***	-0.91***	-0.88***	-0.94***	-0.67**	-0.51*	-0.59	-0.53	-0.48*	-0.38	-0.70*
	(0.39)	(0.22)	(0.28)	(0.25)	(0.28)	(0.30)	(0.28)	(0.38)	(0.38)	(0.28)	(0.25)	0.41
Standardized PPVT score												
Birth weight (log)	0.52***	0.75***	0.81***	0.99***	1.06***	1.12***	1.02**	1.27	0.94	1.39	0.80	1.09**
	(0.17)	(0.21)	(0.21)	(0.26)	(0.28)	(0.42)	(0.46)	(0.87)	(1.08)	(0.90)	(0.88)	(0.53)
Low birth weight	-0.43***	-0.63***	-0.58***	-0.80***	-0.87***	-0.92***	-0.85**	-1.08	-0.81	-1.24	-0.68	-0.896*
	(0.16)	(0.20)	(0.19)	(0.15)	(0.23)	(0.35)	(0.40)	(0.73)	(0.90)	(0.76)	(0.80)	(0.505)

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, and probability of exclusive breastfeeding.
*p< 0.10, **p<0.05, ***p<0.01

Table A6: Robustness to missing information on birth weight: 2SLS effect of low birth weight (LBW) on PPVT z-score

	Assuming missing sample			
	Baseline	Non-LBW	LBW	17% are LBW
	(1)	(2)	(3)	(4)
Low birth weight (dummy)	-0.905*	-1.12**	-2.10	-1.16**
	(0.505)	(0.518)	(1.69)	(0.524)
Cluster fixed effects	Yes	Yes	Yes	Yes
Sample selection term	Yes	Yes	Yes	Yes
R-squared	0.38	0.36	-0.12	0.27
Observations	1609	3748	1609	3699

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, and probability of exclusive breastfeeding.
*p< 0.10, **p<0.05, ***p<0.01

Table A7: 2SLS effects by birth weight categories

	PPVT score (log)	PPVT z-score	F-stat	N
	(1)	(2)	(3)	(4)
< 2500 grams	-0.501	-0.949	3.12	259
	(0.733)	(1.007)		
2500+ grams	2.342*	3.159*	4.42	1262
	(1.281)	(1.900)		
2500 grams or less	1.081	1.801*	2.62	656
	(0.668)	(0.968)		
> 2500 grams	1.098	0.799	2.24	865
	(1.728)	(2.581)		
Log(BW), 0-3000 grams	0.782	1.285*	4.83	1213
	(0.512)	(0.717)		

Notes: Robust standard errors, clustered at the community level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural residence, probability of exclusive breastfeeding, sample selection term (inverse mills ratio), and cluster dummies.
*p< 0.10, **p<0.05, ***p<0.01