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ABSTRACT

Birth Weight and Cognitive Development during Childhood: Evidence from India*

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 scores 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 girls, children from rural 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 Classification: I12, I15, I18, J13, J24, O12

Keywords: birth weight, test score, cognition, PPVT, children, instrumental variable, India

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1. Introduction

Low birth weight (LBW), weighing less than 2,500 grams, is a significant public health challenge in resource-poor countries as it is directly related to the sustainable development goal of good health and well-being. Around 20.5 million newborns, an estimated 15-20% of all infants born globally are LBW (WHO, 2014). Previous studies show that LBW infants have a higher mortality risk in their first month of life and those who survived face worse health, human capital, IQ, and labor market outcomes (Behrman and Rosenzweig, 2004; Figlio et al., 2014, Bhardwaj, Eberhard, and Nielson, 2018).[1] An estimated 18% of Indian infants are born as low birth weight (LBW) babies, the second-highest rate in South Asia (IIPS, 2015).

India has made tremendous progress in improving school enrollment (96%) in the last decade, yet learning outcomes remain poor and are on the decline 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% of 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). An important constraint to learning and human capital formation in developing countries is poor childhood health as studies have shown that health endowment at birth, as indicated by low birth weight (LBW), affects later-life health, schooling, and economic outcomes (Currie and Vogl, 2013). 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

[1]Other important studies in this area include, see Oreopoulos *et al*. (2006), Black, Devereux, and Salvanes, (2007), Royer (2009), Almond and Currie (2011).

Although there is considerable evidence on the effects of low birth weight on adult outcomes, the evidence on mid-childhood outcomes through which the adult outcomes manifest is limited. Compared to adult outcomes, mid-childhood outcomes are more policy-relevant because the birthweight effects on adult outcomes manifest through the mid-childhood years and adult outcomes take many years to appear and therefore are less amenable to policy interventions. The fetal origins literature indicates that the catch-up growth of children is more likely to happen during mid-childhood compared with adulthood due to the gradual scarring of brain cells. Therefore, for effective policy intervention, a better understanding of the developmental trajectories in the intervening period of early- and mid-childhood is important because this period is malleable (Almond, Currie, and Duque, 2018).[2] Another gap in the literature is the limited evidence on the heterogeneous effects of birth weight in a low-income setting, whether the effect of birth weight on cognitive ability varies by age or household characteristics.

This study attempts to fill this gap by estimating the effects of birthweight on cognitive outcomes in the mid-childhood years (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, children's Peabody Picture Vocabulary Test (PPVT) score, a measure of cognitive ability.[3] Estimating the causal effect of birth weight on cognitive development is difficult due to the 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

[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 stimulus words read out by the examiner.

large set of potential confounding factors at the child, mother, and household level. We use a binary indicator of preterm birth (PTB) and the mother's height jointly as instruments.[4] 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.

Studies of the predictive role of birth weight on cognitive ability are largely based in 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 the 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 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

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

children, and therefore, these LBW children might catch up in the long run.[5] 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 on their investment in these children. These behaviors have important implications for the role of complementarities in human capital formation (Cunha and Heckman, 2007). Whether parental inputs and birth endowments 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 for 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 the estimation of heterogeneity in birth weight effects by demographic and socioeconomic characteristics of the households.

We find positive and statistically significant effects of birth weight on the PPVT score: a 10% increase in birth weight increases the PPVT score by 8.1% and the PPVT z-score by 0.11. LBW babies have 0.91 standard deviations lower test scores compared with non-LBW babies. The birthweight effect is statistically insignificant at age 5 but becomes statistically significant at age 8, a finding similar to 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, girls, and children of less-educated mothers are more likely to benefit from improved neonatal outcomes. The quantile

[5]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.

regression results show that the effect of birth weight is higher and statistically significant at the lower distribution of the PPVT score.

Our study contributes to the literature on early childhood conditions and human capital accumulation in several ways. First, to the best of our knowledge, this is the first study to explore this topic in India, possibly due to the paucity of 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 model, but these models fail to control for birth order and birth endowment effects. Third, unlike most previous studies that 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, a measure of cognitive ability because cognitive skills rather than school attainment are an important determinant of labor market outcomes in

[6]Two previous studies that use IV method to examine the birthweight effects include Lin, Leung, and Schooling (2017) and Lin and Liu (2009).

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 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, the 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 is 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 monozygotic twins from Minnesota, Behrman and Rosenzweig (2004) find a positive relationship between birth weight and adult height,

[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.

earnings, and schooling attainment in the US. They show that the twin who is heavier by about 1 lb. at birth is likely to be more educated (by 0.7 years), earn 7% more, and is taller by 0.6 inches at age 45 years.[8] Black et al. (2007) confirms 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%. Furthermore, using administrative data from Florida in the United States from 1992 to 2002, Figlio et al. (2014) find that a 10% increase in (log) birth weight is associated with a 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 scores 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 400 grams increase in birth weight led to a 15% standard deviations increase in math test scores

[8] At the mean birthweight of 90.2 oz, one lb. increase in birthweight implies a 17.7% increase.

(Torche and Echevarria, 2011).[9] 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 deviations 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-effect models 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). In general, twins differ from singletons in terms of health endowment as twins are more likely to be premature, have low birthweight, genetic abnormalities. Twin births are also positively associated with the mother's health and healthy behaviors which are likely to affect child quality (Bhalotra and Clarke, 2018). Thus, if twins are more susceptible to higher health risks compared with singletons, then twins' birthweight effect is likely to underestimate the effect of singletons' birthweight. The instrumental variable method on *singletons* sample instead of twins could deal with these concerns of unobserved heterogeneity in a better way.

Two studies based on the 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. Whereas Lin et al. (2017) use genetic variants (single nucleotide polymorphisms) and twin status as instruments and

[9] 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).

found no association between birthweight and academic attainment in adolescence among Chinese children in Hong Kong. Nakamuro et al. (2013) employs twin fixed-effect and find positive impacts of birth weight on academic performance at age 15 but no effects on the highest years of schooling and earnings in Japan. In another Taiwanese study, using sibling and twin fixed-effects Xie et al. (2017) show positive and significant impacts on medium- and long-term schooling outcomes. The medical evidence on the association between birth weight and cognitive development is discussed in Appendix A.

In summary, in addition to high-income countries especially the USA and the Nordic countries; only a small number of empirical studies have examined the effects of birth weight in a few Asian countries such as China, Hong Kong, Japan, and Taiwan as well. However, 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 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 scores, particularly in the mid-childhood phase of the life cycle in India.

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 dynamic nature of childhood poverty and its consequences on adult outcomes in four LMICs – Ethiopia, India, Peru, and Vietnam – over 15 years. 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 community 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. The cognitive outcomes were measured by the PPVT score and the Cognitive Developmental Assessment Quantitative (CDA-Q) at age 5 in round 2. However, in round 3 the CDA-Q test was replaced by a mathematics test. Since only the PPVT test was comparable between the two rounds, we use the PPVT score as the main outcome variable.

The Indian YL survey sampled 2,011 6-18 months and 1,008 eight years old children. The sample is selected from 20 community sites spread across three agro-climatic zones (Coastal Andhra Pradesh, Rayalaseema, and Telangana) in the southern state of Andhra Pradesh.[10] Our analysis uses the sample of the younger cohort from the first three rounds of the YL survey: the baseline round in 2002 and two follow-ups in 2006 and 2009 when the average ages of the younger 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. Round 1 data is used for the birthweight and exogenous control variables, while round 2 and 3 data are used for the outcome variable at age 5 and age 8, respectively. This

[10] Since the YL survey oversampled children from poorer areas of Andhra Pradesh to understand the causes and consequences of childhood poverty, the YL sample is less likely to be nationally representative.

provides a sample size of 1776 (868x2) children. Finally, we drop children with missing observations in any of the explanatory variables used in our main analysis, which leaves us with the main sample of 1,611 children for the pooled model. 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 was administered to the younger 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 PPVT is a widely used test to measure verbal ability and general cognitive development (see Crookston et al. (2013); Paxson & Schady (2007)), and the PPVT test score is positively correlated with other common measures of intelligence such as the Wechsler and McCarthy Scales (Campbell 1998).

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 and to have better goodness of fit (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. The control variables are 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). This is in contrast to the near consensus in high-income countries that earlier-born children have higher IQ and schooling than their later-born siblings. This happens because earlier-born children are more likely to join the labor market to support household income. In a developing country context, where child labor is prevalent, the effects of birth order are the opposite of the effects in developed countries. 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), and rural residence. 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).

Although breastfeeding duration is positively associated with education and cognitive development in Andhra Pradesh (Nandi et al., 2017) and elsewhere (Anderson et al., 1999), our model does not include breastfeeding because it is endogenous and likely to be affected by the birthweight. We only include pre-treatment control variables (i.e., before birth) in the model to avoid endogeneity issues due to the inclusion of post-treatment covariates.

The analysis includes community fixed-effects to control for time-invariant characteristics such as overall development (visible and invisible infrastructures) of the communities. 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 was 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:

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

where each observation is for individual child i in household j in sentinel s. Sentinel/community 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 (< 2,500 grams). C_{ijs} denotes child characteristics, H_{js} denotes household characteristics, θ_s is sentinel/community fixed-effects, and μ_{ijs} are the idiosyncratic error terms.

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. Previous studies have either used twins or siblings fixed-effect models to address these concerns of unobserved heterogeneity (Figlio et al., 2014;

Bharadwaj et al., 2018). 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

We estimate the following two-stage least square (2SLS) models in the instrumental variable framework. The first and second-stage regressions are of the following form:

First stage:

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

Second stage:

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

Where 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, and rural), θ_s represents sentinel or community 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 communities. Standard errors are clustered at the child level, which account for the fact that the same child is included in the model twice.[11] 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

[11] It should be noted that we cannot estimate the model with child fixed-effects because the birthweight variable does not vary over time. Only the outcome variable is longitudinal and varies over time.

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 instruments used in this study are the *mother's height* and a binary indicator of *preterm birth* (PTB), which we argue that instruments are plausibly exogenous and affect the outcome variables only through birthweight. 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 or 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 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 guides its choice as the instrument in our study.

Mother's height is correlated with pregnancy outcomes because maternal height affects the physical environment of the uterus (shorter women may have smaller uterus size) and may reflect the 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 empirically established. The exclusion restriction requires orthogonality between the instruments and the dependent variables conditional on other explanatory variables and does not assume unconditional orthogonality. Therefore, 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 A2. We discuss the results on the instrument's relevance and excludability condition in more detail in the results section.

Another potential concern is that preterm birth is not completely excludable because premature birth may directly affect brain development, breathing disorders, and brain hemorrhage risks which are likely to affect the learning ability of preterm babies. We are unable to control for these factors, however, this will bias the 2SLS estimates downward. Furthermore, it is possible that maternal height could affect children's cognition directly if taller mothers have higher education or are more likely to be employed. Working mothers may spend less time with their children. In our estimation, we include parents' 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 A3 and discuss them in the results section.

4.4. Sample selection bias

In our study sample, birth weight is observed only for 43% (for 868 children of 2,011 children) 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 A4. Results show that socio-demographic characteristics are different for the two samples. For many variables, the difference between the two samples is statistically significant. We use the Heckman-type correction method (Heckman, 1979) to correct for missingness. 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 the inverse mills ratio as regressors in the 2SLS model.[12]

[12]We predict probability of observing BW using a probit model. The probit model includes birth weight

In a robustness check, we weight the regression 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 rebalances the sample to make it representative of the population. While exploring the reason for missing information on birthweight, 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. For example, BW information is missing for 81% of the home births and 33% of institutional births. Of the total sample of 2,011 children, 1,000 were born at home and the remaining 1,011 children were born at health facilities. Another important determinant of missing data on birthweight was the availability of government birth records. Thus, recording birthweight data in the YL survey was primarily dependent on the place of delivery and government documentation of births. 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 records and births at home.

4.5. 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 affect 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

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documentation, parental education, rural residence, household wealth, and home births as explanatory variables to predict BW missingness.

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 wealth.

Additionally, subgroup analyses to estimate heterogeneous effects are 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 32.34 and 64.61, 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. 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 13% 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 rounds 2 and 3, respectively, with 45% of them being female. The average age is 80 months in the pooled sample.

The average birth order is 1.8; mothers are less likely to be educated compared to fathers, as the primary school completion rate among mothers is 58% while it is 66% among fathers. The average mother's height is 151.4 centimeters. Households are predominantly rural (58%) and practice the Hindu religion (84%). About 25% of the children belong to socially disadvantaged communities (scheduled social group/scheduled tribe) and 53% of them belong to the top wealth group. 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 define the rich as the top wealth group.

5.2. First-stage of IV results

The first-stage regression shows the predictive power of our two instruments, the 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 the mother's height is less than 10 in column 1, suggesting that the instrument is weakly correlated with BW.[13] 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 12.77, 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 12.77 and the Cragg-Donald Wald F statistics is 33.02. The F-test shows that the two instruments are strong, statistically significant, and robust to the inclusion of covariates and community fixed effects.

Although the IV condition of excludability is difficult to test statistically, we provide indirect checks in Table A2. Results in Table A2 indicate that the preterm sample of children is similar to the full-term sample on several socioeconomic and sociodemographic characteristics. Of the 21 variables in Table A2, 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 the preterm sample has more educated and wealthy parents. It is unclear in which direction the significant difference in parental characteristics will bias

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

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 behavior variables are significantly different. The remaining variables are also similarly distributed across the two categories in Table A2.

We also test for overidentification restrictions in Table 2 and Table A3. The Sargan-test p-value and Basmann p-value are mostly above 0.10, implying that both instruments could be included in the IV models (Table 2). Table A3 reports the results from the regression of 2SLS residuals on the instruments and the exogenous variables as suggested by Wooldridge (2010). The R-squared in Table A3 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 community fixed effects to capture time-invariant characteristics of the communities and inverse mills ratio to correct for sample selection biases. Column 1 shows the OLS estimates, and columns 2-4 report 2SLS estimates. 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 the PPVT score by 1.9% (column 1).[14]

Columns 2 and 3 report the results from the 2SLS models when BW is instrumented by the mother's height and preterm birth, respectively. Results in columns 2-3 indicate that

[14]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.

BW is positively associated with the log of the PPVT score; however, the estimates are statistically significant only in column (3). The results in column 3 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 (4) when BW is instrumented by both instruments - mother's height as well as preterm births. The 2SLS results in column (4) show that BW has a statistically significant causal effect on the PPVT score. The estimated 2SLS coefficient is 0.801, meaning an increase of BW by 10% will raise the log(PPVT) score by 8.0%. The 2SLS coefficient is about four times larger than the OLS estimate. The difference between the OLS and the 2SLS coefficients implies 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 (4), we lose a few observations due to missing information. The coefficient on the inverse Mills ratio in column (4) is statistically insignificant (not reported), implying that selection of children into the estimation sample is not a major concern.

For ease of interpretation, the literature in education frequently uses standardized test scores rather than the raw or log of the test scores as the dependent variable.[15] In Table 4, we report the effect of birth weight on standardized PPVT scores (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 (2)-(4). Results are statistically insignificant when we use the mother's height as the instrument (column 2), whereas results in columns (3) and (4) pass the statistical

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

significance at a 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 the mother's height as well as preterm births together as instruments in column 4, 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 community 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, panel B in Tables 3 and 4, 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, respectively. The OLS and the 2SLS results show that LBW is negatively associated with both the outcome variables. Column 4 in Table 3 shows that low birth weight children have a 65% lower PPVT score compared to children who are not low birth weight. Results in column 4 in Table 4 shows that LBW children have 0.9 SD lower test scores compared to non-LBW children. The 2SLS coefficient is about five times larger than the OLS estimates.[16]

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 5, we conduct a similar analysis by age of the 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 PPVT 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 the ages at which the effects of birth weight start appearing. Whether the birthweight effects set in early childhood or mid-childhood ages remain an important inquiry?

Bharadwaj et al. (2018) find that the effect of birth weight 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).[17] Our

[16]The results in column 4 are slightly bigger in magnitude. Column 4 in Table 3 shows that low birth weight children have 65% 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 4 is that an increase in BW by ~547 grams (or by 28% [547/1954]) could increase log of PPVT score by 65%. The average BW among LBW infants is 1,954 grams in our analytical sample.

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

results in Table 5 show that the negative effects of poor birth outcomes do not appear by age 5 (columns 1 and 3) but are statistically significant and economically meaningful at age 8. For example, a 10% increase in birth weight increases standardized test scores 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 grades 2 or 3 in 2009. This implies that the birth weight effect in our study starts appearing in grades 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 a 1.09 SD lower test score relative to children who are not LBW (Panel B, Table 5). In summary, poor neonatal health is not a statistically significant determinant of test scores at age 5 but plays an important role in predicting the PPVT score at age 8. However, the results for other cognition-related outcomes are mixed (Table A6). The birth weight has positive effects on CDA-Q at age 5 but there is no evidence of statistically significant effects on math test scores 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 robust causal association between birth weight and test scores in the Indian YL sample. Nonetheless, the effects of birth weight on test scores may vary by child and household characteristics. On the one hand, if 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 6 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 the log(PPVT) score and column 2 shows the results for the standardized PPVT score. It should be noted that the *F-stat* and *N* would be identical for models in columns (1) and (2) because first-stage regressions are the same for both outcomes. To save space, we only report the 2SLS results.[18] The pooled 2SLS coefficients are statistically significant for rural, girls, less educated mothers, and poor households sample. For example, the birthweight effect on the PPVT z-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 richer households than the poorer 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 girls and not for the boys. In

[18]The OLS results are available upon request.

contrast, neither Bharadwaj et al. (2018) nor Figlio et al. (2013) found any evidence of a differential effect of BW on test scores 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. Instrumental variable quantile regression results

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 reported in Tables 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 scores are stronger (weaker) at higher (lower) quantiles. Figure 1 reports the estimates for the quantiles {0.20, 0.40, 0.60, 0.80}, whereas Table A7 reports the results for 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 scores are statistically significant mostly at the lower and the median quantiles. An increase in birth weight raises test scores 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 scores 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 the robustness, we examine the stability of our main findings in two ways. First, instead of employing a Heckman-type correction method, we use inverse probability weighting to correct for selection bias. Columns (1) and (3) in Table 7 report the results of this analysis. The control variables in Table 7 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 the log(PPVT) score by 8.7% (column 1) against the benchmark estimates of 8.01% 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 (column 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 a jackknife instrumental variable estimator (JIVE) that is more robust to weak instrument problems as well as the correlation among multiple instruments (Angrist, 2004). Results in columns (2) and (4) in Table 7 indicate that our main findings are quite stable and robust to the estimation of an alternative version of the IV method, the JIVE approach. 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 A8, we further show that our main results on LBW (panel B in Tables 3 & 4) are robust to non-inclusion of observation, which had missing birth weight information. Although we correct for the sample selection bias through the Heckman-type correction method or inverse probability weighting, we bound the 2SLS estimates for LBW analysis in Table A8. Column (1) provides the benchmark coefficient from Table 4. 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.[19] 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 1.24 SD, 37% 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).[20]

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 A9. Results are very sensitive to the heaping of birth weight at 2,500 grams and clear evidence of non-linear effects does not emerge from this analysis. In many cases, the estimates are statistically insignificant. However, for completeness, we report these results as well.

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

[20]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.

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 the 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 example, large-scale educational interventions (financial incentives to teachers, remedial education, and computer-assisted learning) increased test scores 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 the 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, girls, poor, and children born to less-educated mothers. 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 variation in the birth weight or household fixed-effects model due to a lack of 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 of the state or the country as a whole. Third, mothers' 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 limitations. Data on gestational weeks is available only for preterm births and the lack of similar information for full-term births precludes us from including gestational weeks as an additional control in our preferred specification. Despite these limitations, we believe that the findings from this study will engender health policy design to improve neonatal outcomes in India.

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. Improving access to prenatal care and maternal nutrition could be important interventions to reduce the risk of premature births and low birthweight in low-income countries. Prenatal care is critical for ensuring improved birth outcomes as infants born to mothers who received prenatal care are less likely to be low birth weight. (Gonzalez and Kumar, 2018). Additionally, parents' compensatory behavior, postnatal interventions, 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 can identify and design cost-effective policies for children of different ages.

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Table 1: Summary Statistics

	Mean	S.D.	N
	(1)	(2)	(3)
Outcome variables			
PPVT raw score at age 5 (2006)	32.34	24.59	795
PPVT raw score at age 8 (2009)	64.61	32.65	816
PPVT raw score (pooled)	48.68	33.14	1611
PPVT z-score (pooled)	0.181	1.08	1611
Log of raw PPVT score (pooled)	3.64	0.71	1611
CDA-Q at age 5 (2006)	9.74	2.66	826
Math score at age 8 (2009)	13.45	6.36	821
Explanatory variables (Round 1, 2002)			
Low birth weight	0.168		868
Birth weight (grams)	2763.65	547.13	868
Log of birth weight	7.90	0.21	868
Instrumental variables (Round 1, 2002)			
Mother's height	151.46	6.91	838
Preterm birth (PTB)	0.13		828
Child characteristics			
Age of child (in months), 2006	64.21	4.01	838
Age of child (in months), 2009	95.51	3.83	830
Age of child (in months, pooled)	80.09	16.11	1611
Birth order	1.81	0.95	868
Female (%)	0.46		868
Household characteristics (Round 1, 2002)			
Mother is primary schooled (%)	0.58		868
Father is primary schooled (%)	0.66		868
Rural (%)	0.58		868
Hindu (%)	0.84		868
Rich (%)	0.53		868
Schedule caste and tribe (%)	0.25		868
Communities (#)	20		
Districts (#)	6		
Regions (#)	3		

Notes: Standard deviations are shown in parenthesis only for continuous variables

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*
	(0.001)		(0.0009)
Preterm birth		-0.123***	-0.122***
		(0.027)	(0.027)
Weak identification test			
Kleibergen-Paap Wald rk F statistic	4.10	21.32	12.77
Cragg-Donald Wald F statistic	7.48	61.92	33.02
Tests of overidentifying restrictions			
Sargan test p-value			0.685
Basmann p-value			0.688
p-value for endogeneity test			0.092

Notes: Robust standard errors, clustered at the child 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, inverse mills ratio, and community fixed effects.
*p< 0.10, **p<0.05, ***p<0.01

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

	PPVT score (log)			
	OLS	Two-Stage Least Squares		
		Instrument: Mother's height	Instrument: Preterm birth	Instruments: Mother's height + Preterm birth
	(1)	(2)	(3)	(4)
Panel A: Birth weight (log)	0.195***	1.68	0.717**	0.801**
	(0.060)	(1.12)	(0.359)	(0.358)
R-squared	0.50	0.33	0.48	0.47
Observations	1609	1609	1521	1521
Panel B: Low birth weight	-0.112***			-0.654**
	(0.031)			(0.329)
R-squared	0.50			0.43
Observations	1609			1521

Notes: Robust standard errors, clustered at the child level, are in parentheses. All models include community fixed effects and inverse mills ratio. *Controls*: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, and rural location.
*p< 0.10, **p<0.05, ***p<0.01

Table 4: OLS and 2SLS effect of birth weight on standardized test scores

	PPVT z-score			
	OLS	Two Stage Least Squares		
		Instrument: Mother's height	Instrument: Preterm birth	Instruments: Mother's height + Preterm birth
	(1)	(2)	(3)	(4)
Panel A: Birth weight (log)	0.244**	1.67	1.03**	1.08**
	(0.102)	(1.58	(0.56)	(0.547)
R-squared	0.42	0.35	0.40	0.39
Observations	1609	1609	1521	1521
Panel B: Low birth weight	-0.160***			-0.896*
	(0.046)			(0.50)
R-squared	0.42			0.37
Observations	1609			1521

Notes: Robust standard errors, clustered at the child level, are in parentheses. All models include community fixed effects and inverse mills ratio. *Controls*: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, and rural location.
*p< 0.10, **p<0.05, ***p<0.01

Table 5: 2SLS effect, by child's age

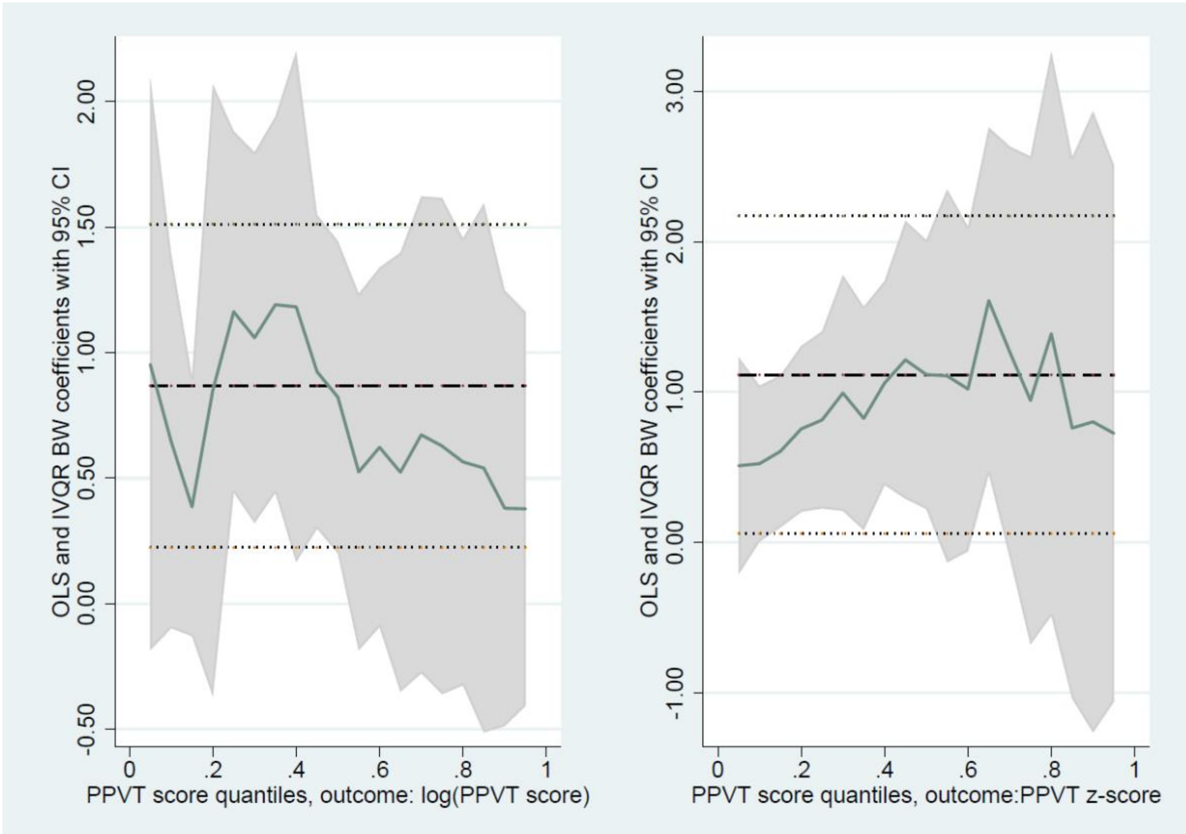
	PPVT score (log)	PPVT score (log	PPVT z-score	PPVT z-score
	Age 5	Age 8	Age 5	Age 8
	(1)	(2)	(3)	(4)
Panel A				
Birth weight (log)	1.05	0.564***	0.867	1.287**
	(0.789)	(0.219)	(1.034)	(0.573)
R-squared	0.29	0.25	0.46	0.47
Panel B				
Low birth weight (dummy)	-0.843	-0.473**	-0.702	-1.091**
	(0.722)	(0.208)	(0.891)	(0.485)
R-squared	0.19	0.22	0.42	0.44
Community 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, and rural location.
*p< 0.10, **p<0.05, ***p<0.01

Table 6**:** 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	0.889	0.662	4.41	625
	(0.738)	(1.138)		
Rural	0.623**	1.155**	10.14	896
	(0.352)	(0.561)		
Boys	0.694*	1.049	9.03	809
	(0.406)	(0.636)		
Girls	1.345**	1.619*	5.30	712
	(0.693)	(0.954)		
Mother is primary schooled	0.429	0.329	7.13	877
	(0.506)	(0.803)		
Mother is not primary schooled	1.149***	1.88***	10.03	644
	(0.432)	(0.671)		
SCST	1.076	1.782	0.77	339
	(1.755)	(2.634)		
Other social group	0.567*	0.841	11.67	1182
	(0.326)	(0.518)		
Poor	0.825	1.192	6.40	754
	(0.530)	(0.749)		
Rich	0.811*	1.011	9.40	767
	(0.460)	(0.722)		

Notes: Robust standard errors, clustered at the child level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural location, inverse mills ratio, and community fixed effects. *F-stat* and *N* are the same for columns (1) and (2) because models in columns (1) and (2) have the same first-stage.
*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 1: Instrumental variable quantile regression (IVQR) results

Table 7: Robustness Checks (IV estimates)

	PPVT score (log)		PPVT z-score	
	IPW	JIVE	IPW	JIVE
	(1)	(2)	(3)	(4)
Birth weight (log)	0.869**	1.499*	1.189*	2.087*
	(0.406)	(0.772)	(0.615)	(1.184)
Community 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 child level, are in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, and rural location. *Instruments:* Mother's height and Preterm birth
*p< 0.10, **p<0.05, ***p<0.01

Appendix

A. Birth weight and cognitive development

There are two complementary hypotheses to explain the significant association between low birth weight and adult outcomes. The foremost explanation is based on the "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 channels. 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 has detrimental effects on neurodevelopmental 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).

Table A1: Validity test: Observable predictors of preterm birth and mother's height

	Mother's height	Pre-term births
	(1)	(2)
Female child	0.073	-0.073***
	(0.457)	(0.025)
Birth order	0.071	-0.036
	(0.351)	(0.023)
Child was wanted	-1.156	0.007
	(0.896)	(0.039)
Mother's age at birth	-0.002	0.004
	(0.096)	(0.004)
Maternal education	0.434	0.039
	(0.601)	(0.027)
Father's education	0.719	0.026
	(0.488)	(0.037)
Household size	0.109	0.0005
	(0.083)	(0.006)
Household social group (SCST)	-1.380**	0.036
	(0.565)	(0.038)
Rural	3.939***	-0.110***
	(0.677)	(0.037)
Hindu religion	-1.401**	0.017
	(0.694)	(0.037)
Household wealth (top tercile)	0.816*	-0.005
	(0.480)	(0.024)
Food shortage	0.664	0.091
	(1.361)	(0.060)
Antenatal care	-0.304	-0.008
	(0.642)	(0.029)
Skilled birth attendant	-0.175	0.011
	(0.615)	(0.034)
Observations	838	822

Notes: OLS coefficients and the robust standard errors, clustered at the child level, are reported in columns 1 and 2, respectively. Cluster fixed effects included in columns (1) & (2). *p< 0.10, **p<0.05, ***p<0.01

Table A2**:** 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 (0.609)
PPVT score (age 8)	61.7	65.02	-3.3 (0.337)
Female child	0.31	0.48	-0.17*** (< 0.001)
Birth order	1.65	1.84	-0.19** (0.05)
Child was wanted	0.95	0.92	0.03 (0.27)
Parent's characteristics			
Maternal age (years)	22.10	22.08	0.013 (0.98)
Maternal education (more than primary school)	0.71	0.57	0.15*** (0.004)
Maternal height	151.07	151.52	-0.46 (0.517)
Father education (more than primary school)	0.77	0.65	0.12** (0.01)
Household's characteristics			
Household size	4.95	5.18	-0.25 (0.27)
Household social group (SCST)	0.28	0.24	0.04 (0.359)
Rural	0.44	0.60	-0.16*** (<0.001)
Hindu religion	0.81	0.84	-0.02 (0.525)
Household wealth (top tercile)	0.65	0.52	0.136** (0.007)
Food shortage	0.05	0.03	0.02 (0.215)
Education expenditure (monthly)	449.3	456.7	-7.39 *(*0.479)
Health preferences and behaviors			
Exclusive breastfeeding	0.81	0.77	0.04 (0.392)
Antenatal care	0.78	0.77	0.01 (0.904)
Skilled birth attendant	0.92	0.86	0.06 (0.101)
Took two or more tetanus shot during pregnancy	0.85	0.86	-0.005 (0.90)
Took iron tablet during ANC visit	0.83	0.84	-0.01 (0.80)
Took folic syrup in the last 3 months	0.75	0.79	-0.04 (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 A3: Test for overidentifying restrictions

	Dependent variable: Estimated residuals from the second-stage equation	
	Coefficient	Robust standard error
	(1)	(2)
Preterm birth	0.007	0.069
Mother's height	0.001	0.003
Age	0.000	0.001
Female	0.000	0.045
Birth order	-0.000	0.025
Maternal education	-0.0005	0.057
Father's education	-0.002	0.054
Rural	0.001	0.105
Scheduled caste and tribe	0.002	0.059
Hindu religion	0.001	0.087
Household wealth (Rich)	-0.000	0.061
Community fixed effects	Yes	
Inverse mills ratio	Yes	
R-squared	0.0001	
Observations	1521	

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

Table A4: 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 A5**:** 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	1.88	2.27**	0.422
	(1.23)	(1.28)	(0.974)	(1.11)
F-stat	1.49	2.70	21.63	1.56
Community fixed effects	Yes	Yes	Yes	Yes
Inverse mills ratio	Yes	Yes	Yes	Yes
R-squared	0.45	0.40	0.49	0.47
Observations	123	177	343	117

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, and rural location.
*p< 0.10, **p<0.05, ***p<0.01

Table A6: 2SLS effects of birth weight on CDA-Q and Math score

	CDA-Q (log)	CDA-Q (log)	Math score (log)	Math score (log)
	Age 5	Age 5	Age 8	Age 8
	(1)	(2)	(3)	(4)
Panel A				
Birth weight (log)	0.701**		-0.328	
	(0.337)		(0.462)	
Low birth weight (dummy)		-0.532*		0.345
		(0.298)		(0.416)
Community fixed effects	Yes	Yes	Yes	Yes
Inverse mills ratio	Yes	Yes	Yes	Yes
Observations	776	776	774	774

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, and rural location. CDA-Q is available only at age 5, while math score is available only at age 8.
*p< 0.10, **p<0.05, ***p<0.01

Table A7: 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 are reported in parentheses.
Controls: Gender, birth order, and age of the child, household caste, father and mother's education, religion, household wealth, rural location, community fixed effects.
*p< 0.10, **p<0.05, ***p<0.01

Table A8: 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)	-0.896*	-1.248**	-2.622	-1.16**
	(0.50)	(0.605)	(2.051)	(0.524)
Community fixed effects	Yes	Yes	Yes	Yes
Inverse Mills ratio	Yes	Yes	Yes	Yes
Observations	1521	3581	3581	3699

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

Table A9: 2SLS effects by birth weight categories

	PPVT score (log)	PPVT z-score	F-stat	N
	(1)	(2)	(3)	(4)
Log (BW)				
< 2500 grams	-0.552	-1.007	1.90	259
	(0.665)	(0.957)		
2500+ grams	2.344**	3.155*	4.91	1262
	(1.174)	(1.797)		
2500 grams or less	1.086	1.801*	4.09	656
	(0.764)	(0.968)		
> 2500 grams	1.116	0.825	2.51	865
	(1.421)	(2.133)		
1000-3000 grams	0.783	1.289*	4.84	1213
	(0.512)	(0.716)		

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