Brain vs. Brawn: Child Labor, Human Capital Investment, and the Role of Dynamic Complementarities

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Abstract

Early-life interventions are a promising route to improve educational outcomes. Yet, in many low-income countries, children (and their parents) make trade-offs between schooling and productive work. We formalize this trade-off in a simple model of human capital investment. If early-life investments increase child wages more than they increase the returns to education, children who receive greater early life investments will attend less school. Exploiting rainfall shocks as a source of variation in early-life income in India, we test the model. Parental income shocks early in a child's life lead to higher educational attainment in places with low levels of child labor, but this positive effect is attenuated in areas with high child labor. When child labor is especially prevalent, positive early shocks have statistically significant, negative effects on educational attainment. To verify that this is not driven by the unobservable characteristics of high child labor regions, we replicate this pattern using geographic variation in two child labor intensive crops, cotton and sugar.

JEL Codes: O12, I2, J1

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1 Introduction

Policies that increase human capital investment during the critical period, ages zero to five, when the developing brain is most plastic (Knudsen et al., 2006), are a promising tool to increase overall human capital attainment. Beyond the high returns of these early interventions, a growing literature focusing on "dynamic complementarities" in the human capital production function suggests that early skills beget more skills by increasing the returns of later human capital investments (Cunha and Heckman, 2007; Gilraine, 2017; Agostinelli and Wiswall, 2016; Johnson and Jackson, 2017). However, in places where children and adolescents work productively (in the market, on the family farm, or in home production), if there are returns to human capital in that work, a higher initial stock of human capital could increase the *costs* of educational investments as well. Thus, actions taken by parents and children can undo the positive educational effects of these interventions by altering their human capital investments in response to positive early-life shocks (Malamud et al., 2016). While much of the literature on early-life investment has focused on these investments in high-income countries,[1] understanding how parents and children respond to positive early-life shocks is particularly important in low-income countries, where child labor is common (Bharadwaj et al., 2013).

In this paper, we provide novel evidence that increased early-life health inputs also increase the opportunity cost of schooling by increasing the returns to child labor in rural India. Thus, the direction of the effect of early-life investments on educational and even long-term wage outcomes will depend on two countervailing forces: (1) how much the early-life investments increase the returns to child labor and (2) how much they increase the returns to later educational investments (the size of dynamic complementarities). By increasing the opportunity cost of schooling, the existence of child labor can mitigate the positive effects of early-life shocks on later schooling. In extreme cases, positive early life human capital shocks

[1] Attanasio et al. (2015), which estimates the human capital production function in India, is a notable exception.

can actually reduce overall schooling levels. In contrast with the literature on high-income countries, early life human capital investments aiming to increase long-run human capital accumulation may be counter-productive in low-income contexts with high child labor.

To formalize this intuition, we first develop a simple, three-period theoretical model of human capital investment that allows for both dynamic complementarities in human capital investment and a positive effect of a child's human capital on his or her child labor wages. Then, to test the predictions of the model, following Maccini and Yang (2009) and Shah and Steinberg (2017), we use variation in rainfall shocks when a child is young (in utero to age 2) as an exogenous shock to the initial stock of human capital. In line with the previous literature, we first show that positive rainfall shocks result in greater weight, height, and school-age test scores, indicating that positive shocks improve early-life human capital investment. Additionally, we show that children who experience these positive shocks and work for a wage receive higher wages, indicating that these early-life shocks positively affect the return to work rather than attending school.

Consistent with the existence of dynamic complementarities, we find that positive early-life income shocks increase the likelihood that a child attends school when he or she is school-aged in areas with low baseline levels of child labor. However, this positive effect is attenuated in districts with higher baseline levels of child labor. In districts in the top quintile for baseline levels of child labor, the sign is reversed, and the overall effect of a positive income shock in early-life on education is significantly negative for schooling.

Since high child labor districts may differ from low child labor districts on a variety of dimensions, we then show that our results are robust to utilizing variation in the pervasiveness of child labor induced by "technological variation." We focus on sugar and cotton, two crops known to be labor intensive and particularly prone to using child labor. Using adult shares of employment in these industries, we classify districts as sugar or cotton producers and find that being a sugar/cotton producer is highly predictive of child labor levels. When we compare the effects of positive early life rainfall in these districts to the effects in non-sugar/cotton producers, we find the same pattern as before. In sugar and cotton producing districts, the positive early-life investments facilitated by positive rainfall shocks decrease the likelihood of attending school during childhood. In non-sugar/cotton producing districts, the opposite is the case.

Our results stress the importance of accounting for the effect of early-life investments on the opportunity cost of schooling, as well as the returns to schooling in low-income countries. From a policy perspective, If the policymaker's objective is to increase schooling, investing in early-life interventions without complementary interventions to reduce child labor may be counterproductive. Taking the effect of early-life investments into account is also important for researchers characterizing the human capital production function in low-income countries. If we draw inferences about the human capital production function from high child labor areas, without taking into account the opportunity cost of schooling, we would falsely conclude that later human capital investments' returns are decreasing in early investments. On the other hand, if we focus on low child labor areas, our results would be consistent with dynamic complementarities.

These results contribute to a growing literature on the opportunity cost of schooling in both developed (Charles et al., 2015; Cascio and Narayan, 2015) and developing countries (Shah and Steinberg, 2017, 2018; Atkin, forthcoming). This paper is also related to the literature on dynamic complementarities, which was theoretically introduced by Cunha and Heckman (2008), and tested empirically in several different contexts (Gilraine, 2017; Agostinelli and Wiswall, 2016; Johnson and Jackson, 2017; Cunha and Heckman, 2007). While our paper does not directly test for the presence of dynamic complementarities in the human capital production function, we do illustrate an important additional channel through which earlier human capital investments might impact later schooling choices—child labor.

The paper proceeds as follows. Section 2 provides further background on child labor in India and describes the data used in the analysis in this paper. Section 3 describes the theoretical framework. Section 4 presents our empirical strategy and tests the predictions of the model for wages, education and child labor, allowing early-life shocks to have differential effects by the baseline child labor in a district. Section 5 concludes.

2 Background and Data

2.1 Background on Child Labor in India

Although child labor for children 14 and under was officially banned in India in 1986, the ban covered only certain industries and was not well enforced.[2] Importantly, agriculture and family-run businesses – perhaps the chief employers of child labor – were exempted from the ban. Beyond the various exemptions, there is some evidence that the ban itself may have increased child labor through negative income effects (Bharadwaj et al., 2013).

Overall, child labor is common in India, as it is in many low-income countries. According to the NSS, 5% of children under 18 report working as their primary activity, while 22% of individuals 15–17 do so. Figure 1 shows the variation in the percent of children under 18 who report working as their primary activity across Indian districts. The most common industries for these children are agriculture and construction. Shah and Steinberg (2017) show that child labor responds to productivity shocks, suggesting that wages are an important determinant of whether children work. Finally, while some children work in the labor market for pay, most work part-time at home or on family farms.

2.2 Data

2.2.1 Main Outcomes: Child Labor, School Attendance

We use the National Sample Survey (NSS) to measure our main outcomes of interest: school attendance and work. The National Sample Survey is a repeated cross section of an average

[2]Industries banned included occupations involving the transport of passengers, catering establishments at railway stations, ports, foundries, handling of toxic or inflammable substances, handloom or power loom industry, and mines. Processes banned included hand-rolling cigarettes, making or manufacturing matches, explosives, shelves, and soap, construction, automobile repairs, and the production of garments (Bharadwaj et al., 2013).

of 100,000 Indian households a year, conducted by the Indian government. We use Schedule 10 (Employment and Unemployment) from rounds 60, 61, 62, and 64 (2004, 2004-5, 2005-6, and 2007-8) in our main analysis. The survey asks each member of the household for their "primary activity," and includes categories for school attendance, wage labor, salaried work, domestic work, etc. We count a child as "attending school" if their primary activity is listed as attends school, and "works" if their primary activity is any form of wage/salary labor, work with or without pay at a "home enterprise" (usually a farm, but also includes other small family businesses), or domestic chores. These two categories comprise most of the primary activities of children under 18, though there are other categories that are omitted, such as too young/infirm for work (typically the very old and very young), and "other," which includes begging and prostitution.

In addition, in order to understand whether the interaction between early-life investment and the presence of a market for child labor can affect the opportunity cost of schooling, we need a measure of child labor by district. For that measure, we use the 2000 (round 57) NSS. Our primary measure of child labor is the fraction of children (age 0-18) who report their primary activity as work in a district. We will also use the share of cotton and sugar production in the district (since those two crops have the highest proportion of child workers) as a proxy for child labor.

2.2.2 Secondary Outcomes: Child Labor, Wages, Test Scores and Anthropometrics

For additional data on child labor wages and activities, we turn to the India Human Development Survey (IHDS), a repeated panel dataset that was implemented in 2005 and 2012. This survey also measures child height, weight and cognitive abilities, and these data allow us to test the assumption that children with higher human capital earn higher wages in the market. We further supplement the IHDS and the NSS with data from ASER, which includes test scores for a large cross-section of children – including those who are out of school – from 2005–2009.

2.2.3 Variation in Human Capital: Yearly Gridded Rainfall

Our data on rainfall shocks come from the University of Delaware Gridded Rainfall Data for 1970-2008. Following earlier literature (Shah and Steinberg, 2017; Jayachandran, 2006), we define a "rainfall shock" as equal to one if rain is in the top 20th percentile for the district, -1 if it is in the bottom 20th percentile, and 0 otherwise.[3] We match this data to children in the NSS, the IHDS, and ASER by their birth year at the district level. To verify that our implicit first-stage (that rainfall affects agricultural wages) is relevant, we also match this data to World Bank data on crop yields from 1975–1987.

Table 1 documents our different data sources and the key variables from each source.

3 Model

We develop a simple model of human capital investment in the presence of child labor. The model clarifies the circumstances under which positive early-life human capital investments can reduce schooling, even in the presence of dynamic complementarities in the human capital production function. We first show that the early-life income shocks caused by positive rainfall shocks lead to increased early-life human capital investment. If there are dynamic complementarities, this human capital investment positively affects the returns to later schooling investment, incentivizing parents to invest more in later-education. However, in places where child labor is prevalent, early-life investments also affect the child wage, which is the opportunity cost of schooling. This countervailing force attenuates the positive effect of early-life investment on schooling. In extreme cases, early-life investments increase the child wage more than they increase the returns to education, causing schooling to fall. We document this with greater formality in the next two sub-sections, which first present the set-up of the model and then derive propositions.

[3] In India, though flooding does happen, more rain is almost always better for crop yields. This is well documented in Jayachandran (2006).

3.1 Set Up

The decision-maker in the model is a parent, and each parent has one child. The decision-maker is indexed by her child's educational ability, α, which is distributed according to the function F and her type of district, $d \in \{low, high\}$. d denotes whether a parent is in a high or low child labor district. There are three periods in the child's life: early life, school age, and adulthood, and α becomes observable in period 2, when a child is old enough to attend school. The parent lives for the first two periods. In period 1, they decide how much to invest in a child's early-life human capital, h. In period 2, they make a discrete decision whether or not to educate the child, $e \in \{0, 1\}$, or have the child work for a wage $w^c_{2,d}(h)$. Child wages depend on both early-life investment h and d. The discrete educational investment maps to the fact that children either primarily work or attend school in our data, rather than moving between working and education on a continuum. The parent consumes in both periods and also have some altruism toward their child's third period, adult utility. Suppressing the indices α and d, a parent's preferences in period 1 are represented by

$$U^p_1(h) = u(c^p_1(y_1, h)) + E\left(\max_e u(c^p_2(y_2, e, h)) + \delta U^c(c^c_3(e, h))\right),$$

where c^p_1 and c^p_2 are the parent's consumption in periods 1 and 2, c^c_3 is the child's adult consumption in period 3, u is the utility function, U^c is the child's adult utility, which depends on educational and early-life investments, δ is the product of the parent's discount rate and her altruism toward the child, and the expectation is taken over realizations of α. Both u and U^c are assumed to have diminishing marginal returns in consumption.

Similarly, the parent's period 2 utility is given by

$$U^p_2(h, e) = u(c^p_2(y_2, e, h)) + \delta U^c(c^c_3(e, h)).$$

For simplicity, the model abstracts away from borrowing and saving. Then, parental consumption in period 1 is equal to some exogenous income y_1 net the cost of human capital investment h. Parental consumption in period 2 is total income, y_2, net the cost of schooling if $e = 1$ or plus the wages from child labor if $e = 0$. Thus,

$$
\begin{aligned}
c_1^p &= y_1 - c_h h \\
c_2^p &= y_2 + (1-e)w_{2,d}^c(h) - c_e e \\
c_3^c &= w_3^c(e,h) + \alpha e
\end{aligned}
$$

where c_h is a cost of the human capital investment and c_e is the cost of education. $w_3^c(e,h)+\alpha e$ is the child's total adult wage, where the function $w_3^c(e,h)$ allows for a flexible relationship in adult wages between e and h. Following Cunha and Heckman (2008), there are dynamic complementarities in the adult wage function if $\frac{\partial w_3^c(1,h)}{\partial h} > \frac{\partial w_3^c(0,h)}{\partial h}$. This captures the idea that early life investments in human capital make educational investments more productive. The wage expression also allows children to heterogeneously benefit from schooling based on their schooling ability, α.

Before solving the model, we make several assumptions to simplify exposition. First, we assume that $w_{2,low}^c(h) = 0$, so that if child labor in a district is negligible, child wages are always equal to zero. In places where child labor is high, we assume $\frac{\partial w_{2,high}^c}{\partial h} > 0$. This assumption captures the idea that early-life human capital investments increase child wages. We directly test this assumption in our data in the next section.

3.2 Predictions

We now solve for the parent's equilibrium investment decisions, and relate them to changes in first period income y_1.

Proposition 1. *Denote h^* as the parent's equilibrium choice of h. If $w_{2,d}^c(h)$ and $w_3^c(e,h)$ have diminishing marginal returns in h, $\frac{\partial h_d^*}{\partial y_1} > 0 \, \forall d$.*

Proof. See Appendix A.

The first proposition indicates that a positive income shock in early life will increase early-life human capital investment. The intuition for this prediction is straightforward. When y_1 increases, the marginal utility of first period consumption falls, increasing the parent's incentive to invest in her child's human capital. This proposition is consistent with the previous findings of Shah and Steinberg (2017) and Maccini and Yang (2009), who show that an early life shock increases test scores and weight.

Building on Proposition 1, the next set of propositions develop the key predictions of the paper – that early life shocks increase education rates in places with low child labor and have no effect on or even decrease education rates in places with high child labor.

Proposition 2. *Denote $\lambda_d(y_1)$ to be the share of children educated in a district of type d given y_1. $\frac{\partial \lambda_{low}(y_1)}{\partial y_1} > 0$ only if $\frac{\partial w_3^c(1,h)}{\partial h} > \frac{\partial w_3^c(0,h)}{\partial h}$.*

Proof. See Appendix A.

This proposition captures the fact that, in low child labor places, increased h only positively affects the parent's educational decisions through its effect on the returns to later-life educational investments. Therefore, if an early life shock increases educational investments in low child labor markets, this is evidence in favor of the fact that early life investments increase the returns to later educational investments. However, as predictions 3a and b show, in high child labor markets, positive early life investments can have zero or negative effects, despite their potential positive effect on the returns to education due to dynamic complementarities.

To introduce Proposition 3a, we first note that for a given value of h, the parent will educate a child if $U_2^p(h,1) \geq U_2^p(h,0)$. Since $\frac{\partial U^p(h,1)}{\partial \alpha} > 0$ and $\frac{\partial U^p(h,0)}{\partial \alpha} = 0$, this relationship exhibits single-crossing. Thus, for any combination of h and d, there exists a cut-off value $\alpha_d^*(h)$ for α where $e = 1$ for all children with $\alpha \geq \alpha_d^*(h)$. Figure 2 illustrates this by plotting the ability distribution, F, and showing that $e = 1$ if $\alpha > \alpha_d^*(h)$.

Proposition 3a. *If $\frac{f(\alpha^*_{high}(h^*_{high}(y_1)))}{f(\alpha^*_{low}(h^*_{low}(y_1)))} < \Phi$, $\frac{\partial \lambda_{high}(y_1)}{\partial y_1} < \frac{\partial \lambda_{low}(y_1)}{\partial y_1} \forall I$.*

Proof. See Appendix A.

This proposition indicates that a positive income shock increases education (and adult wages) more in low child labor districts than high child labor districts, as long as the fact that increased returns to the parent from child labor dominate two other, second order effects with ambiguous directions. This is captured by the assumption $\frac{f(\alpha^*_{high}(h^*_{high}(y_1)))}{f(\alpha^*_{low}(h^*_{low}(y_1)))} < \Phi$.[4] The effect we expect to dominate is that an increase in h increases the relative returns to education more in low child labor areas because, in high child labor areas, increasing h also increases the outside option, $w^c_{2,d}$. The additional ambiguous effects come from the fact that (1) the density of children on the margin of being educated is different in high and low child labor regions since enrollment rates are different, and (2) the derivative of adult wages with respect to early childhood investment may be different in high and low child labor regions if underlying investment in h is different in these regions. If underlying early-life human capital investment rates are similar and the densities of the distribution at $\alpha^*_d(h_d(y_1))$ are similar across these regions, these additional effects will be small.[5]

Figure 3 illustrates the intuition for proposition 3a. In both high and low child labor districts, the increase in y_1 increases the relative returns to schooling, causing $\alpha^*_d(h^*_d))$ to fall. But α^*_{low} falls more than α^*_{high} because the relative returns to schooling increase more in low child labor districts. The share of children whose educational outcomes are changed is captured by the gray areas, which integrate over the ability distribution from the old to the new values of α^*_{low} and α^*_{high}. Even though the density at the cut-off is different in high and low child labor districts, as long as it is not too much greater in high child labor districts, more children will be affected in low child labor districts, where the integral is taken over a larger set of values of α. While proposition 3a shows that the effects of early-investment on the

[4] $$\Phi = \frac{\frac{\partial w^c_3(h^*_{low},1)}{\partial y_1} - \frac{\frac{\partial w^c_3(0,h^*_{low})}{\partial y_1} U^{c\prime}(w^c_3(0,h^*_{low}))}{U^{c\prime}(w^c_3(1,h^*_{low})+\alpha^*_{low})}}{\frac{\partial w^c_3(1,h^*_{high})}{\partial y_1} - \frac{u'(y_2+w^c_{2,high}(h^*_{high}))\frac{\partial w^c_{2,d}(h^*_{high})}{\partial y_1} + \delta \frac{\partial w^c_3(0,h^*_{high})}{\partial y_1} U^{c\prime}(w^c_3(h^*_{high},0))}{\delta U^{c\prime}(w^c_3(1,h^*_{high})+\alpha^*_{high})}}.$$

[5] The assumption that $\frac{f(\alpha^*_{high}(h(y_1)))}{f(\alpha^*_{low}(h(y_1)))} < \Phi$ bounds how much greater the density at α^*_{low} can be relatively to the density at α^*_{high}. That is, if the density at α^*_{high} is sufficiently high, it can lead the response to shocks to be greater in high child labor places even though the change in the ability cut-off is smaller.

returns to child labor can attenuate the positive effects of early-life investment on schooling, the next proposition shows that in extreme cases, early-life investment can negatively affect schooling.

Proposition 3b. *If* $\frac{\partial w^c_{2,high}(h^*(y_1))}{\partial h}$ *is sufficiently great,* $\frac{\partial \lambda_{high}(y_1)}{\partial y_1} < 0$.

Proof. See Appendix A.

Proposition 3b shows that when the effect on parental utility of the increase in child wages due to an increase in y_1 is sufficiently large in high child labor places, it outweighs the effect of the increase in the returns to education (weighted by the parents' altruism and discount rate). Then, positive income shocks that increase early life investments can lead to reduced education, potentially translating into reduced wages later in life.

4 Empirical Strategy and Results

Our model predicts that children with different initial levels of human capital will make different choices to invest in schooling, and that these choices can depend on the economic environment. To identify these effects, we need variation in both the initial stock of human capital and the labor market for children. We will address these issues step-by-step. First, in Section 4.1, we will show that rainfall shocks experienced early in life provide a plausibly exogenous shock to the initial stock of human capital, consistent with previous work (Maccini and Yang, 2009; Shah and Steinberg, 2017). In Section 4.2, we show that these differences in human capital affect child wages, and thus their opportunity cost of education. Secondly, in Section 4.3 we show that these differences in the initial stock of human capital cause differential investment in education during childhood. Third, in Section 4.3, we show that these responses to human capital stock differ based on the prevalence of child labor in the district—in places with low child labor, children with high initial stocks of human capital are significantly more likely to be in school during childhood and in places with the highest child labor, children are less likely to be in school and more likely to be working. This is consistent with both dynamic complementarities in the human capital production function and a return to human capital in the market for child labor. Lastly, in Section 4.4, we use crop shares as a more exogenous source of variation in child labor and find similar results.

4.1 Variation in Early-Life Human Capital

To test the implications of the model, we use early life rainfall shocks as a proxy for shocks to early-life human capital. The existing literature provides a strong argument for this relationship. The argument is as follows: positive rainfall shocks increase yield, which increases parental wages, as shown by Jayachandran (2006) and Kaur (forthcoming). Intuitively, and as we also demonstrate in Prediction 1 of our model, higher parental wages lead to higher early-life investment (Maccini and Yang, 2009 and Shah and Steinberg, 2017). This could take the form of increased nutrition for pregnant or breastfeeding mothers, increased medical care during infancy, more parental time spent fostering development, etc.

Our data are consistent with these hypotheses. As Appendix Table A1 shows, positive rainfall shocks increase yield. Here, a rainfall shock is coded as 1 if rain is greater than the 80th percentile of the distribution from 1975 to 2008, -1 if it is less than the 20th percentile, and 0 otherwise, following Jayachandran (2006). Furthermore, we replicate the positive relationship between rainfall and wages found in the literature in Appendix Table A2.

We next aggregate rainfall shocks into a single child-level measure by taking the sum across the three shocks in-utero, age 1, and age 2. Tables 2 and 3 also confirm that early-life shocks affect human capital in our data, showing that children who experience shocks in utero, in their first year, and in their second year have higher height and weight in the IHDS (Table 2) and better test scores in the ASER (Table 3). These findings confirm Prediction 1 from the model and show that rainfall shocks are a relevant instrument for early-life human capital investment.

4.2 Early Human Capital Investments Affect Child Wages

We next turn to the key assumption of our model, that early-life human capital investments affect the opportunity cost of schooling by increasing child wages. To test whether this is the case, we first use the IHDS to regress child wages on human capital measures with the following specification

$$y_{idta} = \alpha_a + \beta_1 human\ cap_{idta} + \Gamma X_i + \epsilon_{idta},$$

where i denotes a child, a denotes age, t denotes the survey round, d denotes a district, α_a is an age fixed effect, and X_i is the set of controls consisting of gender and district fixed effects. $human\ cap_i$ is our human capital measure, which may be height, weight, or lagged math scores. Thus, β_1 is our coefficient of interest, and we expect it to be positive. We restrict our sample to individuals aged 0–17 and cluster our standard errors at the district-level.

Since our proxies for human capital are likely endogenous, we next instrument for height using our child-level aggregate rainfall shock measure. Our first stage regression is then

$$human\ cap_{idta} = \alpha_a + \lambda_1 ELR_{dta} + \Psi X_i + \upsilon_{idta},$$

where ELR_{iat} is the aggregate rainfall measure.

Table 2 reports the results of these regressions. In both the OLS and the IV, we find a positive relationship between child wages and measures of human capital, supporting the key assumption of the model that human capital investments also affect the outside option.

4.3 Early-Life Investment and Schooling

We now turn to testing the key prediction of our model. Based on Prediction 2, we expect that if there are dynamic complementarities, in districts with low child labor, early life shocks will increase educational investment. In districts with high child labor, this effect will be attenuated (Proposition 3a) and may even be reversed (Proposition 3b), so that early-life shocks *decrease* human capital investment.

We first show graphical evidence that this is the case in Figures 4 and 5. Figure 4 shows the effect of an early life rainfall shock on school attendance for children under 17, separately by the district quintile of average child labor at baseline. In places with low baseline child labor, positive early rainfall shocks increase school enrollment later in childhood. However, as child labor increases, this effect attenuates, and in the districts in the highest quintile of child labor, the effect is reversed, so that children with positive early life shocks are *less* likely to be in school. Figure 5 shows the opposite pattern for children's work: in low child-labor districts, children with positive shocks to human capital are less likely to be working, but in high child-labor districts, they are significantly more likely to be working.

To test whether this is the case, we estimate the following regression

$$y_{idta} = \alpha_a + \beta_1 ELR_{dta} + \beta_2 ELR_{dta} \times CL_d + \gamma_d + \delta_t + \epsilon_{idta}, \tag{1}$$

where y_{idta} now consists of measures of working or being enrolled in school, CL_d is a measure of the child labor in the district (either the percent of children engaged in child labor in the NSS or an indicator variable for the percent being over a cut-off value), γ_d is a district fixed effect, and δ_t is a survey year fixed effect. The remaining variables and subscripts are defined as before.

From Prediction 2, we expect β_1 to be positive if there are dynamic complementarities. Prediction 3a predicts that $\beta_2 < 0$, indicating that the increase in child wages due to early-life human capital investments reduces the positive effect of early-life human capital on investment. Prediction 3 suggests that cases may exist where $\beta_1 + \beta_2 < 0$, indicating that the effect of early-life human capital investment on child wages dominates the effect on the returns to education.

Table 5 reports the results of these regressions. In Panel A, we report estimates for the effect of early life rain on whether a child's primary activity is attending school. On average, children who experience one more positive rain shock early in life are about 0.3 percentage points more likely to attend school each year. As this is the estimated effect on enrollment for the average year, over the course of the 17 years of child life included in the sample, this would lead to a 0.051 year increase in schooling. However, in districts with more child labor, this effect is attenuated. In fact, in the districts in the top quintile of child labor, children who experience more rainfall early in life are significantly less likely to attend school. Each year, a child who receives one more positive rainfall shock is 0.7 ppt less likely to be enrolled. Aggregating up, this is a 0.12 year decrease in a child's schooling. For comparison, a large primary school construction program in Indonesia increased male schooling by 0.12 years (Duflo, 2001), suggesting that these effects are meaningful.

In Panel B of Table 5, we replace school with work as the child's primary activity for the outcome variable. The effects are similar. Children in low child labor districts reduce the likelihood of reporting working by 0.3 ppt, suggesting they work 0.05 fewer years as a result of one additional year of positive rainfall early in life. Children in high child labor places are 0.9 ppt more likely to work, implying that they spend 0.153 more years working in aggregate. The similarly sized (but opposite) effects on working and education suggest that the positive early-life shocks mainly affect children on the margin between work and school.

One potential threat to the validity of these estimates is that baseline child labor levels may be correlated with an omitted variable that causes early life shocks to have smaller (or negative) effects on education for other reasons. Two of the most intuitive candidate omitted variables are income and school quality. For income, high child labor areas could be poorer, so parents are less able to complement positive early-life shocks with later educational investments or complementarities between schooling and educational investment could be smaller because fewer high skilled jobs are available. Similarly, areas with high child labor could have lower school quality, reducing the complementarity between early life human capital and education, and therefore, reducing parents' incentives to invest in education. To account for income, we calculate the average adult wage and share of those who work for a wage for each district at baseline and include the interaction between these controls and ELR_{dta} in equation (1). To account for school quality, we take the average literacy rate in each district and the primary and secondary school completion rates and also include these interactions with ELR_{dta}. Figures 6 and 7 report the total effect of an early life shock in a top quintile child labor district ($\beta_1 + \beta_2 CL_d$) for these new specifications. For both working and attending school, the results are qualitatively similar to those without the controls.

Figures 8 and 9 further explore the distribution of the effects of early-life shocks on education and child labor across age groups. These figures are generated by interacting ELR_{dta} and $ELR_{dta} \times CL_d$ with age fixed effects in equation (1). We then report estimates of the total effect of a positive shock on education and working by age for children in districts in the top quintile for child labor. Consistent with the intuition of the model, children exposed to more positive early life rainfall shocks are neither more likely to work nor drop out until the early stages of adolescence. If anything, preadolescent children exposed to early life rainfall shocks are more likely to remain in school, even in high child labor districts.

4.4 Crop Variation as a Proxy for Child Labor

The share of children working in a given district is itself an equilibrium outcome caused by various attributes of the district and the people who live there. While in the previous section we do not find that our measures of poverty or schooling qualitatively change the patterns, it is possible that we are measuring the (potential) confounders with error, and that they cause the differences in the response of education to early life shocks, rather than child labor itself. To address this, we take advantage of the fact that some crops are easier for children to work on than others, given the nature of the tasks associated with planting, weeding, and harvesting the crops. In the NSS, cotton and sugar are the two crops that have the highest proportion of workers under 18 (around 1/5 of workers in each crop are children at the start of our sample). This is consistent with other contexts; cotton in particular is notorious as a child labor crop because it is low to the ground and very lightweight (Levy, 1985). Cotton and sugar both require somewhat specialized growing conditions, and thus grow in only 20% of districts in India.

We use both the presence of any sugar or cotton crop and the percentage of acreage in the district of each of these crops as a proxy for child labor. In Table 6, we re-estimate our results from Table 5 using this proxy in place of district averages for child labor. These results tell a very similar story. On average, children who experience better early life rain are less likely to be working and more likely to be attending school. However, in places with cotton and sugar, these effects are reversed, and children who experience higher early life rain are *less* likely to be in school and *more* likely to be working.

5 Conclusion

Interventions that increase early-childhood investment may be a powerful tool for increasing educational attainment overall. However, such policies could have counter-intuitive effects in low-income countries, where child labor is common. We provide new evidence that early-life investments increase child wages, increasing the attractiveness of child labor. Furthermore, we document the fact that while early-life investments positively affect educational outcomes in places where child labor is low, consistent with the existence of dynamic complementarities, this effect is attenuated in places where child labor is high. In the places where child labor is the highest, early life interventions may even reduce long-term educational outcomes. These results have important implications both for policy-makers interested in increasing educational outcomes and for researchers interested in identifying the form of the human capital production function. For the latter, our results suggest that researchers, particularly those working in low-income countries, must take into account how child human capital affects the opportunity cost of schooling, as well as the benefits of schooling.

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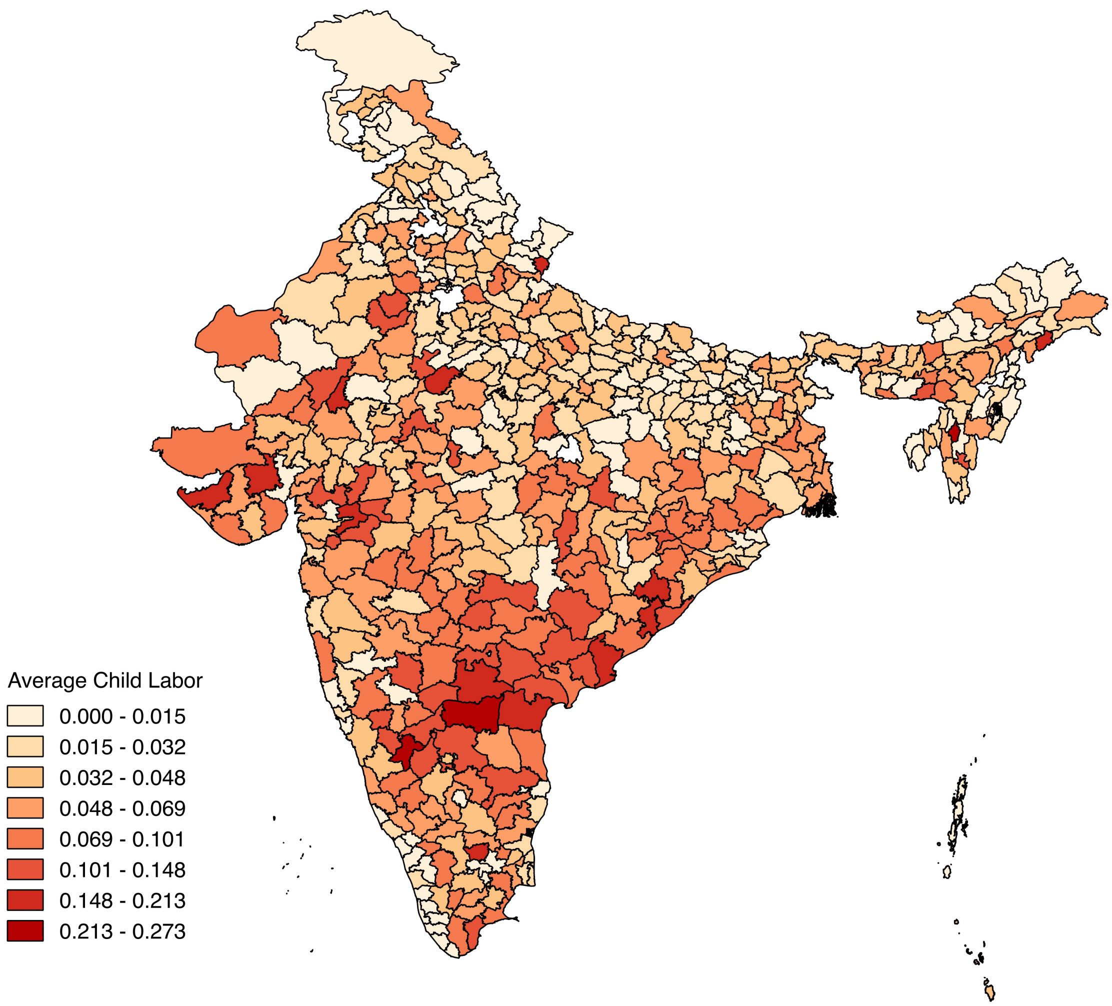
Figures

Figure 1: Distribution of Child Labor by District in the Indian NSS



Source: NSS Round 57 (1999-2000)
Notes: This Figure shows the average level of child labor in each district, where child labor is measured as the fraction of individuals age 0-17 who report their primary activity as working, which includes wage/salary work, work on a home enterprise (such as a farm or small business), or domestic work at home.

Figure 2: The Educational Decision in the Model

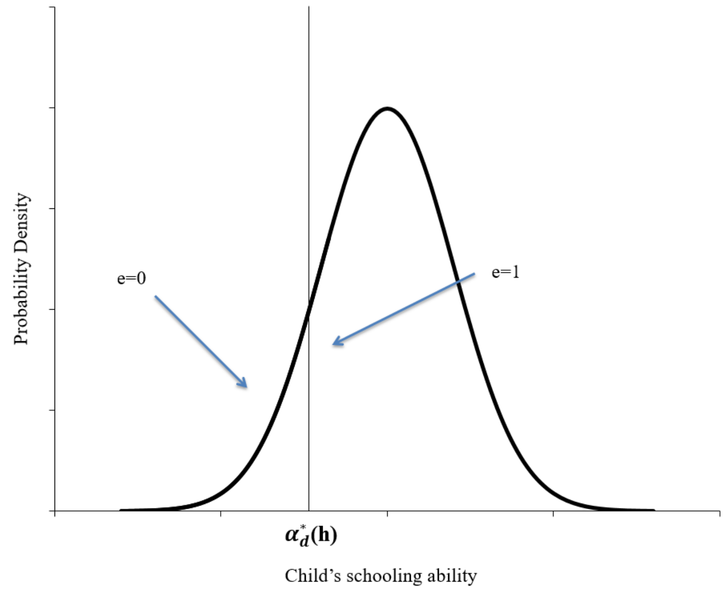


Figure 3: Illustration of Proposition 3a

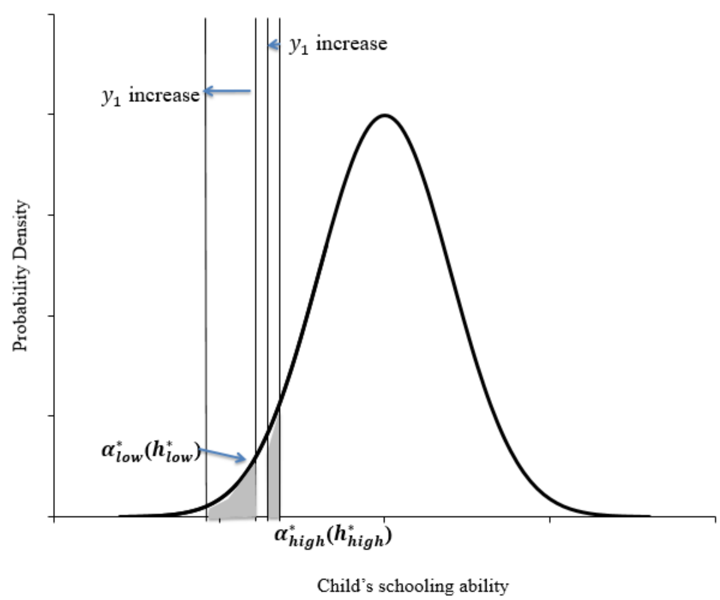
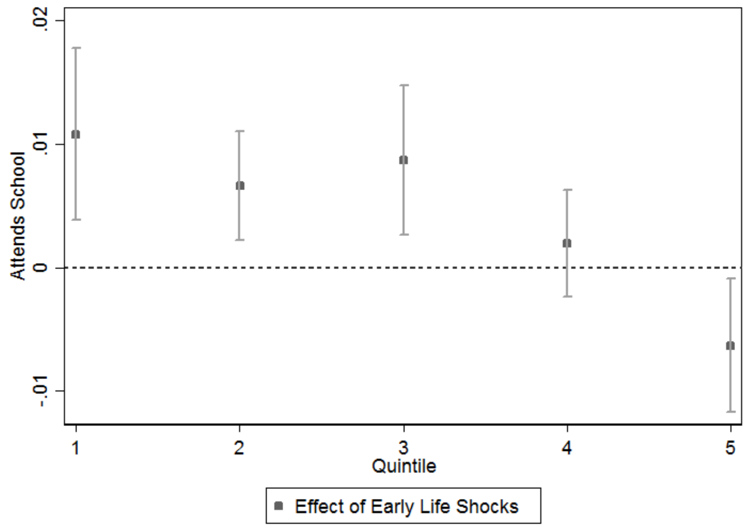
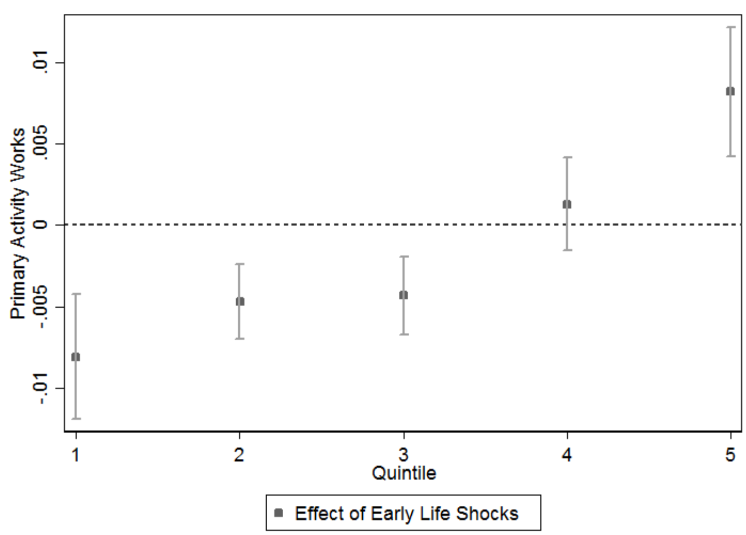


Figure 4: Effect of Early Life Rain on School Enrollment, by Child Labor Prevalence



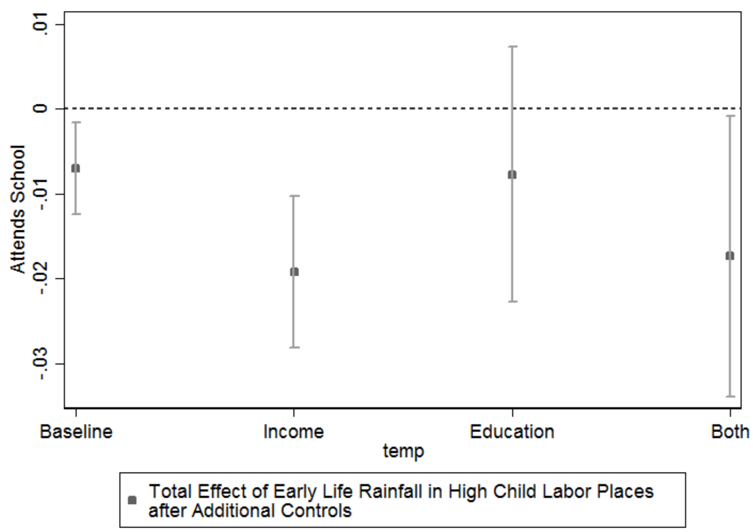
Source: NSS Rounds 60-64 (1999-2008)
Notes: This Figure shows coefficients from a regression of early life rainfall shocks on school attendance, separately for districts in each quintile of average child labor. The outcome variable is as dummy equal to one if a child reports attending school as his/her primary activity, and zero if they report another primary activity. The regressions contain fixed effects for district, child age, and child sex. 95% confidence intervals, clustered at the district level, are shown in brackets.

Figure 5: Effect of Early Life Rain on Working, by Child Labor Prevalence



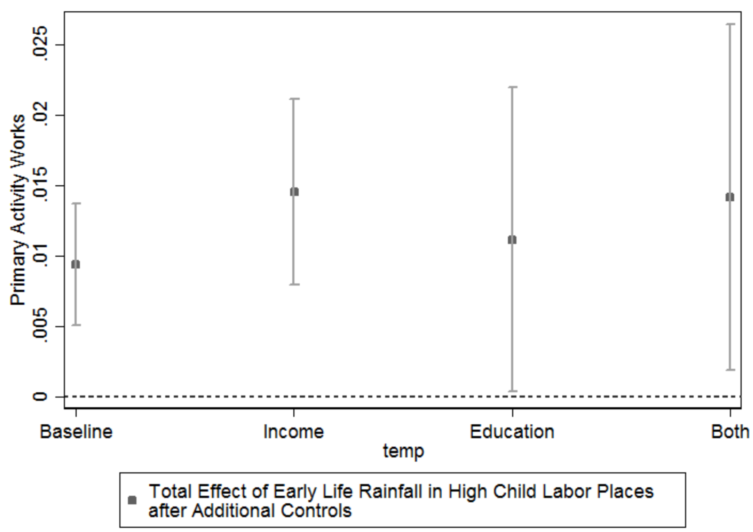
Source: NSS Rounds 60-64 (1999-2008)
Notes: This Figure shows coefficients from a regression of early life rainfall shocks on child work, separately for districts in each quintile of average child labor. The outcome variable is as dummy equal to one if a child reports working as his/her primary activity which includes wage/salary work, work on a home enterprise (such as a farm or small business), or domestic work at home, and zero if they report another primary activity. The regressions contain fixed effects for district, child age, and child sex. 95% confidence intervals, clustered at the district level, are shown in brackets.

Figure 6: Effect of Early Life Rain on School Enrollment, Controlling for additional District Characteristics



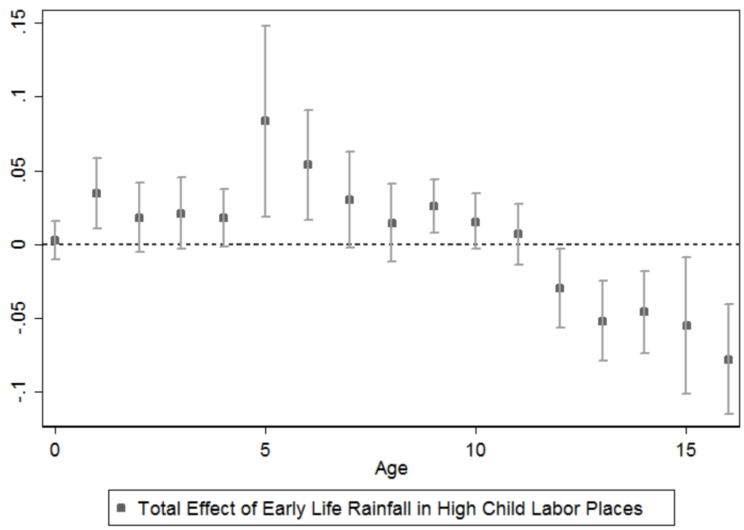
Source: NSS Rounds 60-64 (1999-2008)
Notes: This Figure shows coefficients from a regression of early life rainfall shocks on school attendance with additional controls. The outcome variable is as dummy equal to one if a child reports attending school as his/her primary activity, and zero if they report another primary activity. Additional controls include schooling controls (district average literacy rate, primary school completion rate, and secondary school completion rate) interacted with early life shock, and income controls (share of adults who work for a wage and average wage) interacted with early life shocks. The regressions contain fixed effects for district, child age, and child sex. 95% confidence intervals, clustered at the district level, are shown in brackets.

Figure 7: Effect of Early Life Rain on Working, Controlling for additional District Characteristics



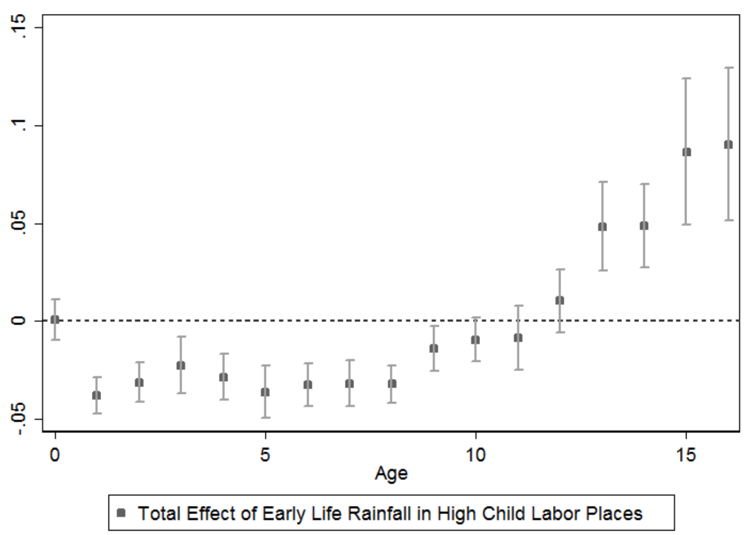
Source: NSS Rounds 60-64 (1999-2008)
Notes: This Figure shows coefficients from a regression of early life rainfall shocks on child work with additional controls. The outcome variable is as dummy equal to one if a child reports working as his/her primary activity which includes wage/salary work, work on a home enterprise (such as a farm or small business), or domestic work at home, and zero if they report another primary activity. Additional controls include schooling controls (district average literacy rate, primary school completion rate, and secondary school completion rate) interacted with early life shock, and income controls (share of adults who work for a wage and average wage) interacted with early life shocks. The regressions contain fixed effects for district, child age, and child sex. 95% confidence intervals, clustered at the district level, are shown in brackets.

Figure 8: Effect of Early Life Rain on School Enrollment, by Age



Source: NSS Rounds 60-64 (1999-2008)
Notes: This Figure shows coefficients from a regression of early life rainfall shocks on child work separately for each age. The outcome variable is as dummy equal to one if a child reports attending school as his/her primary activity, and zero if they report another primary activity. The regressions contain fixed effects for district and child sex. 95% confidence intervals, clustered at the district level, are shown in brackets.

Figure 9: Effect of Early Life Rain on Working, by Age



Source: NSS Rounds 60-64 (1999-2008)
Notes: This Figure shows coefficients from a regression of early life rainfall shocks on child work separately for each age. The outcome variable is as dummy equal to one if a child reports working as his/her primary activity which includes wage/salary work, work on a home enterprise (such as a farm or small business), or domestic work at home, and zero if they report another primary activity. The regressions contain fixed effects for district and child sex. 95% confidence intervals, clustered at the district level, are shown in brackets.

Tables

Table 1: Data Sources

Data Source	**Type**	**Years**	**Variables Used**
National Sample Survey (NSS)	Repeated Cross-Section	2000/2004-2008	avg. child labor primary activity
Annual Status of Education Report (ASER)	Repeated Cross-Section	2005-2009	drop-outs
India Human Development Survey (IHDS)	HH Panel	2005 and 2012	child wages anthropometrics math scores
World Bank India Agriculture and Climate Data Set	District Panel	1975-1987	crop yields
University of Delaware Gridded Rainfall Data	District Panel	1970-2008	rain shocks

Table 2: Relationship Between Child Human Capital and Wages in the IHDS

Dependent Variable:	Log Child Wages			
Height	.0077			.0089
	(.0021)***			(.0038)**
Weight		.0065		.0023
		(.0023)***		(.0044)
Lagged Math Scores			.0228	.0134
			(.0258)	(.0309)
Ages	0-17	0-17	15-17	15-17
Mean DV	14.5	14.5	15.4	15.4
Observations	1,302	1,296	880	695

Source: Data on wages, height and weight come from the IHDS II (2012-13) and lagged math scores from IHDS I (2005-6)
Notes: This table shows coefficients from an OLS regression of the natural logarithm of wages on measures of human capital. Height is measured in centimeters and weight is measured in kilograms. Lagged math scores range from 0-4, and are available only for those adolescents in 2012-13 who were age 8-11 in 2005-6, and able to be matched to IHDS-I. All regressions include gender and age fixed effects. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 3: Effect of Early Life Rain on Size and Test Scores

Dependent Variable:	Height	Weight	Math Score	Math Word Problem	Read Score
Rainshock in Utero	.293	.115	.014	.0049	.017
	(.0874)***	(.071)	(.0044)***	(.0042)	(.0043)***
Rainshock in Year of Birth	.2752	.0193	.011	.0078	.011
	(.1015)***	(.0701)	(.0045)**	(.0044)*	(.0045)**
Rainshock in Year After Birth	.215	-.0497	.014	.018	.016
	(.0881)**	(.065)	(.0043)***	(.0046)***	(.0043)***
Ages	5-17	5-17	5-16	5-16	5-16
Mean DV	125.97	27.55	2.63	1.26	2.72
Observations	36,953	37,409	2,351,596	844,619	2,363,553

Source: Data on height and weight come from the IHDS II (2012-13), data on test scores from ASER (2005-9), and data on rainfall from the University of Delaware
Notes: This table shows coefficients from an OLS regression of measures of human capital on early life rain. Height is measured in centimeters and weight is measured in kilograms. Math and reading test scores range from 0-4, and math word problem ranges from 0-2. Rainshock is equal to one if yearly rainfall is above the 80th percentile for the district, negative one if rainfall is below the 20th percentile, and zero otherwise. All regressions contain fixed effects for sex, age, year and district. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level. Data: IHDS 2012-13 & University of Delaware.
All regressions contain district, year, gender and age FE.

Table 4: Effect of Early Life Rain on Work and Wages

	(1)	(2)	(3)
		ln(wages)	
	Full Sample	Boys	Girls
Early Life Rain	0.020**	0.025**	-0.005
	(0.010)	(0.013)	(0.016)
Mean Outcome	5.34	5.44	5.13
Number Districts	492	464	289
Number Observations	6,858	4,540	2,208

Source: NSS Rounds 60-64 (1999-2008)

Notes: This table shows coefficients from a regression of the natural logarithm of wages on early life rain. Early life rain is the sum of rainshock in the first three years after conception (in utero-age 1), where rainshock is equal to one if yearly rainfall is above the 80th percentile for the district, negative one if rainfall is below the 20th percentile, and zero otherwise. Wages are only measured for children who report positive wage earnings. All regressions contain fixed effects for sex, age, year and district. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 5: Effect of Early Life Shocks on School and Work in High Child Labor Districts

Panel A: School Attendance				
	(1)	(2)	(3)	(4)
	Attends School			
Early Life Rain	0.003**	0.008***	0.006***	0.005***
	(0.001)	(0.002)	(0.002)	(0.001)
Early Life Rain × Child Labor		-0.120***		
		(0.025)		
Early Life Rain × (Above Median) Child Labor			-0.007***	
			(0.002)	
Early Life Rain × (Top Quintile) Child Labor				-0.012***
				(0.003)
Mean Outcome	.602	.602	.602	.602
P Value for Total Effect = 0		.001	.522	.012
Number Districts	552	552	552	552
Number Observations	386923	386923	386923	386923
Panel B: Working				
	(1)	(2)	(3)	(4)
	Primary Activity Works			
Early Life Rain	-0.001	-0.007***	-0.005***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Early Life Rain × Child Labor		0.129***		
		(0.021)		
Early Life Rain × (Above Median) Child Labor			0.009***	
			(0.002)	
Early Life Rain × (Top Quintile) Child Labor				0.012***
				(0.002)
Mean Outcome	.04	.04	.04	.04
P Value for Total Effect = 0		.004	.002	0
Number Districts	552	552	552	552
Number Observations	406179	406179	406179	406179

Source: NSS Rounds 60-64 (1999-2008) and data on rainfall from the University of Delaware
Notes: This table shows coefficients from a regression of primary activity on early life rain, interacted with measures of child labor prevalence by district. In Panel A, the outcome variable is “attends school”, which is equal to one if a child reports their primary activity as attending school, and zero if they report something else. In Panel B, the outcome variable to “works”, which is equal to one if a child reports any productive activity as his primary activity (such as wage/salary work, home enterprise, or domestic work), and zero if he reports something else. Early life rain is the sum of rainshock in the first three years after conception (in utero-age 1), where rainshock is equal to one if yearly rainfall is above the 80th percentile for the district, negative one if rainfall is below the 20th percentile, and zero otherwise. The measure of child labor is the percent of children age 0-17 in the district in NSS round 57 (1999-2000) who report working as their primary activity. All regressions contain fixed effects for sex, age, year and district. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 6: Effect of Early Life Shocks on School and Work in Cotton/Sugar Districts

	(1)	(2)	(3)	(4)	(5)	(6)
	Primary Activity Works			Attends School		
Early Life Rain	-0.001	-0.006***	-0.002*	0.003**	0.007**	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)
Early Life Rain × Sugar/Cotton		0.009**			-0.007	
		(0.004)			(0.005)	
Early Life Rain × Has Sugar/Cotton			0.004**			-0.008***
			(0.002)			(0.003)
Mean Outcome	.04	.04	.04	.603	.603	.603
P Value for Total Effect = 0		.486	.067		.026	.165
Number Districts	564	564	564	564	564	564
Number Observations	409793	409793	409793	390319	390319	390319

Source: NSS Rounds 60-64 (1999-2008) and data on rainfall from the University of Delaware
Notes: This table shows coefficients from a regression of primary activity on early life rain, interacted with measures of child labor prevalence by district. In Panel A, the outcome variable is "attends school", which is equal to one if a child reports their primary activity as attending school, and zero if they report something else. In Panel B, the outcome variable to "works", which is equal to one if a child reports any productive activity as his primary activity (such as wage/salary work, home enterprise, or domestic work), and zero if he reports something else. Early life rain is the sum of rainshock in the first three years after conception (in utero-age 1), where rainshock is equal to one if yearly rainfall is above the 80th percentile for the district, negative one if rainfall is below the 20th percentile, and zero otherwise. The measure of cotton/sugar is the percent of agriculture that is concentrated in these two crops in the district in NSS round 57 (1999-2000). All regressions contain fixed effects for sex, age, year and district. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Appendix Tables

Table A1: High Rain Increases Crop Yields

	Dependent Variable:			
	Rice	Jowar	Maize	Bajra
Rain Shock Current Year	.11	.03	.02	.04
	(.02)***	(.009)***	(.005)***	(.009)***
Year fixed effects	Y	Y	Y	Y
District fixed effects	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	2,987	2,674	2,825	2,297
Mean Dependent Variable	1.51	.589	.282	.291

Source: Agricultural yields from the World Bank India Agriculture and Climate Data Set (1975-1987) and data on rainfall from the University of Delaware
Notes: This table shows coefficients from a regression of crop yields on currents rainshock, where rainshock is equal to one if yearly rainfall is above the 80th percentile for the district, negative one if rainfall is below the 20th percentile, and zero otherwise. All regressions contain fixed effects for year and district, and controls for agricultural inputs. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A2: High Rain Increases Wages

Dependent Variable:	log(wages)
Rain Shock Current Year	.02
	(.009)*
Year fixed effects	Y
District fixed effects	Y
Observations	167,017
Mean Dependent Variable	5.85

Source: NSS Rounds 60-64 (1999-2008) and data on rainfall from the University of Delaware
Notes: This table shows coefficients from a regression of the natural logarithm of adult wages (age 18-64) on current rainshock, where rainshock is equal to one if yearly rainfall is above the 80th percentile for the district, negative one if rainfall is below the 20th percentile, and zero otherwise. Wages are only measured for adults who report positive wage earnings. All regressions contain fixed effects for year and district, and controls for agricultural inputs. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Appendix A

Proof of Proposition 1.

Define $V = E\{\max_e u(y_2 - c_e e + w^c_{2,d}(h)(1-e)) + \delta(U^c(w^c_3(e,h)) + \alpha e)\}$, where the expectation is taken over realizations of α. Then, in period 1, the parent solves

$$\max_h u(y_1 - c_h h) + \beta V(h),$$

where β is the discount rate. h^* must satisfy

$$F = -c_h u'(y_1 - c_h h^*) + \beta \frac{\partial V(h^*)}{\partial h} = 0,$$

To sign $\frac{\partial h^*}{\partial y_1}$, apply the implicit function theorem to F. By the implicit function theorem, $\frac{\partial h^*}{\partial y_1} = -\frac{F_{y_1}}{F_{h^*}}$. Then,

$$F_{h^*} = c_h^2 u''(y_1 - c_h h^*) + \beta \frac{\partial^2 V(h^*)}{\partial h^2},$$

where $c_h^2 u''(y_1 - c_h h^*) < 0$. To sign $\frac{\partial^2 V(h^*)}{\partial h^2}$, observe that

$$\begin{aligned}\frac{\partial^2 V(h^*)}{\partial h^2} =& E\Big(u''(y_2 - c_e e^* + w^c_{2,d}(h)(1-e^*))\Big(\frac{w^c_{2,d}(h)}{\partial h}\Big)^2 \\ &+ u'(y_2 - c_e e^* + w^c_{2,d}(h)(1-e^*))\frac{\partial^2 w^c_{2,d}(h)}{\partial h^2} \\ &+ \delta\Big(U^{c\prime\prime}(w^c_3(h,e^*) + \alpha e^*)\Big(\frac{\partial w^c_3(e^*,h)}{\partial h}\Big)^2 + (U^{c\prime}(w^c_3(e^*,h) + \alpha e^*)\frac{\partial^2 w^c_3(e^*,h)}{\partial h^2}\Big)\Big),\end{aligned}$$

where e^* is the equilibrium choice of e. This expression is < 0 if $\frac{\partial^2 w^c_3(h)}{\partial h^2} \leq 0$ and $\frac{\partial^2 w^c_2(h)}{\partial h^2} \leq 0$. Therefore, $F_{h^*} < 0$. Observe that

$$F_{y_1} = -c_h u''(y_1 - c_h h^*) > 0.$$

Then, it follows from the implicit function theorem that $\frac{\partial h^*}{\partial y_1} > 0$.

Proof of Proposition 2. Given h, a child drops out if $U_2^p(0,h) \geq U_2^p(1,h)$. Substituting in the values for consumption, this expression can be rewritten as

$$u(y_2 + w_{2,d}^c(h)) - u(y_2 - c_e) \geq \delta(U^c(w_3^c(h,1) + \alpha) - U^c(w_3^c(h,0))).$$

The derivative of the LHS with respect to y_1 is $\frac{\partial LHS}{\partial y_1} = u'(y_2 + w_2^c(h))\frac{\partial w_{2,d}^c(h^*)}{\partial h}\frac{\partial h^*}{\partial y_1}$, which is equal to 0 in low child labor places by assumption. The derivative of the RHS is $\frac{\partial RHS}{\partial y_1} = \delta\Big(U^{c\prime}(w_3^c(h^*,1) + \alpha)\frac{\partial^2 w_3^c(h,1)}{\partial h}\frac{\partial h^*}{\partial y_1} - U^{c\prime}(w_3^c(h,0))\frac{\partial w_3^c(h,0)}{\partial h}\frac{\partial h^*}{\partial y_1}\Big)$. From diminishing marginal returns, $U^{c\prime}(w_3^c(h,1) + \alpha) < U^{c\prime}(w_3^c(h,0))$, so for the RHS to be increasing, we need that $\frac{\partial w_3^c(h,1)}{\partial h} > \frac{\partial w_3^c(h,0)}{\partial h}$. This expression implies that, for an early life shock to increase education rates in low child labor areas, there are dynamic complementarities between e and h.

Before proof Proposition 3a, we define Assumption A1.

Assumption A1.

$$\Phi > \frac{f(\alpha_{high}^*(h(y_1)))}{f(\alpha_{low}^*(h(y_1)))},$$

where

$$\Phi = \frac{\frac{\partial w_3^c(h_{low}^*,1)}{\partial y_1} - \frac{\frac{\partial w_3^c(0,h_{low}^*)}{\partial y_1}U^{c\prime}(w_3^c(0,h_{low}^*))}{U^{c\prime}(w_3^c(1,h_{low}^*)+\alpha_{low}^*)}}{\frac{\partial w_3^c(1,h_{high}^*)}{\partial y_1} - \frac{u'(y_2+w_{2,high}^c(h_{high}^*))\frac{\partial w_{2,d}^c(h_{high}^*)}{\partial y_1}+\delta\frac{\partial w_3^c(0,h_{high}^*)}{\partial y_1}U^{c\prime}(w_3^c(h_{high}^*,0))}{\delta U^{c\prime}(w_3^c(1,h_{high}^*)+\alpha_{high}^*)}}$$

Proof of Proposition 3a.

Observe that $\lambda_d(h^*(y_1)) = 1 - F(\alpha_d^*(h_d^*(y_1)))$. Therefore, $\frac{\partial \lambda_d(h_d^*(y_1))}{\partial y_1} = -f(\alpha_d^*(h_d^*(y_1))\frac{\partial \alpha_d^*(h_d^*(y_1))}{\partial y_1}$. To solve for $\frac{\partial \alpha_d^*(h_d^*(y_1))}{\partial y_1}$, note that $\alpha_d^*(h_d^*(y_1))$ is characterized by $U_2^p(0,h_d^*(y_1)) = U_2^p(1,h_d^*(y_1))$, which can be rewritten as

$$u(y_2 + w_{2,d}^c(h_d^*)) - u(y_2 - c_e e) - \delta U^c(w_3^c(1,h_d^*) + \alpha_d^*) + \delta U^c(w_3^c(0,h_d^*)) = 0$$

Applying the implicit function theorem to this expression, we arrive at an expression for $\frac{\partial \alpha_d^*}{\partial y_1}$:

$$\frac{\partial \alpha_d^*}{\partial y_1} = -\frac{\partial w_3^c(1,h_d^*)}{\partial y_1} + \frac{u'(y_2 + w_{2,d}^c(h_d^*))\frac{\partial w_{2,d}^c}{\partial y_1} + \delta \frac{\partial w_3^c(0,h_d^*)}{\partial y_1} U^{c\prime}(w_3^c(0,h_d^*))}{\delta U^{c\prime}(w_3^c(1,h_d^*) + \alpha_d^*)}$$

Substituting this expression into $\frac{\partial \lambda_d(h^*(y_1))}{\partial y_1} = -f(\alpha_d^*(h_d^*(y_1))\frac{\partial \alpha_d^*(h^*(y_1))}{\partial y_1}$, we find that

$$\frac{\partial \lambda_{low}(h_{low}^*(y_1))}{\partial y_1} = \left(\frac{\partial w_3^c(1,h_{low}^*)}{\partial y_1} - \frac{\frac{\partial w_3^c(0,h_{low}^*)}{\partial y_1} U^{c\prime}(w_3^c(h_{low}^*,0))}{U^{c\prime}(w_3^c(1,h_{low}^*) + \alpha_{low}^*)} \right) f(\alpha_{low}^*)$$

$$\frac{\partial \lambda_{high}(h_{high}^*(y_1))}{\partial y_1} = \left(\frac{\partial w_3^c(1,h_{high}^*)}{\partial y_1} - \frac{u'(y_2 + w_{2,high}^c(h_{high}^*))\frac{\partial w_{2,d}^c(h_{high}^*)}{\partial y_1} + \delta \frac{\partial w_3^c(0,h_{high}^*)}{\partial y_1} U^{c\prime}(w_3^c(h_{high}^*,0))}{\delta U^{c\prime}(w_3^c(1,h_{high}^*) + \alpha_{high}^*)} \right) \times f(\alpha_{high}^*)$$

Thus, $\frac{\partial \lambda_{low}(h^*(y_1))}{\partial y_1} > \frac{\partial \lambda_{high}(h^*(y_1))}{\partial y_1}$ under Assumption A1. To provide intuition for when Assumption A1 is satisfied, when h_d^* and α_d^* are sufficiently similar across the two types of districts, $\Phi > 1$. This is because the additional term in the denominator, $u'(y_2 + w_{2,high}^c(h_{high}^*))\frac{\partial w_{2,d}^c(h_{high}^*)}{\partial y_1} > 0$, indicating that the denominator is smaller than the numerator. If α_{low}^* and α_{high}^* are sufficiently similar, $\frac{f(\alpha_{high}^*(h(y_1)))}{f(\alpha_{low}^*(h(y_1)))} \approx 1$ and Assumption A1 will be satisfied.

Proof of Prediction 3b. Recall that $\frac{\partial \lambda_{high}(h_{high}^*(y_1))}{\partial y_1} = -f(\alpha_{high}^*(h_{high}^*(y_1))\frac{\partial \alpha_{high}^*(h_{high}^*(y_1))}{\partial y_1}$, where $f(\alpha_{high}^*) > 0$ and

$$\frac{\partial \alpha_{high}^*}{\partial y_1} = -\frac{\partial w_3^c(1,h_{high}^*)}{\partial y_1} + \frac{u'(y_2 + w_{2,high}^c(h_{high}^*))\frac{\partial w_{2,high}^c}{\partial y_1} + \delta \frac{\partial w_3^c(0,h_{high}^*)}{\partial y_1} u'(w_3^c(0,h_{high}^*))}{\delta U^{c\prime}(w_3^c(1,h_{high}^*) + \alpha_{high}^*)}.$$

Then, $\frac{\partial \lambda_{high}(h_{high}^*(y_1))}{\partial y_1} < 0$ if $\frac{\partial \alpha_{high}^*}{\partial y_1} > 0$. Rearranging $\frac{\partial \alpha_{high}^*}{\partial y_1} > 0$ shows that this satisfied if

$$\delta \left(\frac{\frac{\partial w_3^c(1,h_{high}^*)}{\partial y_1} U^{c\prime}(w_3^c(1,h_{high}^*) + \alpha_{high}^*) - \frac{\partial w_3^c(0,h_{high}^*)}{\partial y_1} U^{c\prime}(w_3^c(0,h_{high}^*))}{u'(y_2 + w_2^c(h_{high}^*))} \right) \left(\frac{\partial h}{\partial y_1} \right)^{-1} < \frac{\partial w_2^c(h_{high}^*)}{\partial h}.$$