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Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital

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Contemporaneous and Long-Term Impacts of
Rainfall Shocks on Human Capital**

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ABSTRACT

Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital*

Higher wages are generally thought to increase human capital production, particularly in the developing world. We introduce a simple model of human capital production in which investments and time allocation differ by age. Using data on test scores and schooling from rural India, we show that higher wages increase human capital investment in early life (in utero to age 2) but decrease human capital from ages 5-16. Positive rainfall shocks increase wages by 2% and decrease math test scores by 2-5% of a standard deviation, school attendance by 2 percentage points, and the probability that a child is enrolled in school by 1 percentage point. These results are long-lasting; adults complete 0.2 fewer total years of schooling for each year of exposure to a positive rainfall shock from ages 11-13. We show that children are switching out of school enrollment into productive work when rainfall is higher. These results suggest that the opportunity cost of schooling, even for fairly young children, is an important factor in determining overall human capital investment.

JEL Classification: O12, I2, J1

Keywords: human capital investment

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1 Introduction

Human capital investment is an important determinant of economic growth (Mankiw et al., 1992). The majority of empirical evidence from poor countries suggests that higher wages should increase human capital investment (see for example, Jacoby and Skoufias (1997); Jensen (2000); Thomas et al. (2004); Maccini and Yang (2009)). However, there is some evidence from Latin America suggesting the opposite (Duryea and Arends-Kuenning, 2003; Schady, 2004; Kruger, 2007).¹ Theoretically, the relationship is ambiguous; if time and income are important inputs into human capital, then increased wages could either increase or decrease human capital investment. As early as 1977, Rosenzweig and Evenson showed that higher wages are associated with lower schooling rates, due to increased opportunity costs of staying in school. If poor children react to higher wages by leaving school early to join the workforce, this could raise overall inequality in poor countries or even stunt long term growth.

Some of the differences in these studies may be due to differential effects by age. If the opportunity cost of time for older children is affected by wages, then the substitution effect would be relatively important for older children. In addition, if the human capital production function itself differs by age (for instance, if income-intensive inputs such as calories are more important for younger children), then we might also observe differential impacts of wage shocks by age.

In this paper, we introduce a simple model of human capital investment in which households derive utility from consumption and human capital. We then estimate the comparative statics from this model, using rainfall fluctuations in rural India as quasi-random shocks to wages. We measure human capital using test scores from the ASER data from 2005-2009; we observe approximately 2 million rural children from almost every rural district in India. The data includes four distinct measures of literacy and numeracy for each child whether

¹All of these papers use school enrollment or years of schooling as their measure of human capital investment.

or not he is currently enrolled in school.² In addition, our data allow us to look at more standard educational measures such as school enrollment, drop out behavior, and being on track in school (age for grade). Since the survey is conducted every year over five years, we can control for age, year of survey, and district, identifying off within-district variation in rain shock exposure.

The estimates of the effect of school-aged wages on human capital suggest that going from regular rainfall to a positive rainfall shock increases wages by 2% and decreases math test scores by 2-5% of a standard deviation, decreases school attendance by 2 percentage points, and decrease the probability that a child is enrolled in school by 1 percentage point. This implies that a positive rainfall shock increases the urban-rural enrollment gap by 15% for 5 to 16 year olds. In addition, children who experienced a positive rainfall shock in the previous year are 5.5% more likely to have dropped out of school and 4.5% more likely to be behind in school.

We also estimate the impacts of early life rainfall shocks (in utero to age 4) on current test scores and schooling outcomes. We find that, by contrast, more early life rainfall is associated with higher test scores in both math and reading. A positive rainfall shock increases wages 2% and increases current test scores for children who experienced a positive rainfall shock in utero to age 2 by about 1.3% of a standard deviation per year of exposure. In addition, children who experience positive rainfall shocks before age 5 are more likely to be enrolled in school and to be on track in school.

We investigate whether there are long-term impacts of these rainfall shocks on total years of schooling for adults aged 16-30 using a national labor and employment survey. We find that more rainfall during school years (particularly ages 11-13) lowers total years of schooling. This is also the age group where positive rainfall shocks significantly increase the likelihood of dropping out as these are the transition years from primary to secondary school so positive employment shocks are particularly detrimental to human capital investment during this

²This is rare since tests are primarily conducted at school, and thus scores are usually only available for currently enrolled kids who attended school on the day the test was given.

period.

As far as we know, this is the first paper to document the possibility that positive productivity shocks can lead to lower levels of human capital attainment using test scores. Test scores measure output as opposed to the previous literature which has focused on school enrollment (i.e. inputs). Unlike the previous literature which focuses on shocks at certain critical ages in a child's development, we consider a child's entire lifecycle from in utero to age 16. This allows us to say something about the relative importance of time vs. income at all stages of a child's human capital development. We show that wages increase human capital investment from the in utero phase to age two, but decrease human capital investment after age 5. In addition, we provide new evidence on the long term effects of cumulative shocks on human capital attainment of young adults. While previous research has suggested that that these shocks represent simple intertemporal substitution of school time and that children make up these differences in human capital (Jacoby and Skoufias, 1997; Funkhouser, 1999), we find quite the opposite. For example, children ages 11-13 complete approximately .2 more years for every drought experienced (and .2 fewer years for every positive rainfall shock relative to normal rainfall years). This constitutes a substantial shock to human capital attainment during a period when most poor children will already be on the margin between dropping out and continuing.

2 A Model of Human Capital Investment

We consider a simple model of human capital investment. Households consist of one child and one parent, and the parent maximizes the total utility of the household. The child lives for three periods. In the first period, the child is too young for school or work and only consumes. In the second period, the child also consumes, but in addition, she has one unit of time that can be spent either in school or working. In the third period, the household gets a payoff from the child's accumulated human capital.

Let c_t be consumption in period t where $t \in \{1, 2\}$, and $u_t(c_t)$ be the flow utility from

consumption in period t , where $\frac{\partial u_t}{\partial c_t} > 0$ and $\frac{\partial^2 u_t}{\partial c_t^2} < 0$, $\forall t$. Let e_t be the human capital of the child in period t , and h be the human capital of the parent, which we assume does not change. Let $V(e_3)$ be the payoff to the household from the level of human capital in period 3. β is the discount factor.³ The total utility function of the household is

$$U(c_1, c_2, e_3) = u_1(c_1) + \beta u_2(c_2) + \beta^2 V(e_3)$$

Let $w_t \in (0, \bar{w})$ denote the wage in period t per unit of human capital, so that parents will be paid $w_t h$ and children will be paid $w_t e_t$ for each unit of time spent working in period t . w_t can be thought of as an aggregate productivity shifter, and in our empirical specifications will be proxied by rainfall in agricultural areas. The wage is determined exogenously. In addition, let $s_2 \in [0, 1]$ denote the time that the child spends in school in period 2, and thus $(1 - s_2)$ will be the time she spends working. In the first period, household income will be earned entirely by the parent, and will be equal to his wage, $w_1 h$. In the second period, the household income will be equal to the earnings of the parent, $w_2 h$ plus the earnings of the child, $(1 - s_2) w_2 e_2$. We will abstract away from borrowing and savings decisions, so that consumption will always be equal to income in each period. Thus, consumption will be

$$c_1 = w_1 h$$

$$c_2 = w_2(h + (1 - s_2)e_2)$$

In the spirit of Cunha and Heckman (2007), we assume that human capital at date t is a function of human capital at date $t - 1$ plus any investments made in period $t - 1$. In this simple model, investments will take the form of either schooling or consumption. We will not allow for directed payments for human capital (such as books or tutors) or for parents to invest their own time to teach children. This is sensible in the context of rural India

³For ease of notation, we assume exponential discounting, even though in this model, the “periods” are of substantially different lengths. This has no effect on our results.

since primary school is free and compulsory,⁴ and the Indian government has built many schools to keep the costs of attendance low.⁵ In addition, the parents of these children often have very low human capital themselves, so it is unlikely that they are heavily involved in teaching their children literacy or numeracy.

In our three period model, human capital in period 1 is normalized to zero, and human capital in period 2 is only a function of the household's consumption in period 1, since the child is too young to attend school in this period. Human capital in period 3, however, will be a function of human capital in period 2, household consumption in period 2, and schooling in period 2. Thus, we have

$$\begin{aligned} e_1 &= 0 \\ e_2 &= f_2(c_1) \\ e_3 &= f_3(e_2, c_2, s_2) \end{aligned}$$

Without loss of generality, we let $V(e_3) = e_3$, $\forall e_3$ for the remainder of the paper.⁶ We assume that $\frac{\partial f_3}{\partial e_2} \geq 0$, $\frac{\partial f_3}{\partial c_2} \geq 0$, $\frac{\partial f_3}{\partial s_2} \geq 0$, and $\frac{\partial f_2}{\partial c_1} \geq 0$. These are standard assumptions asserting that more schooling and consumption result in weakly more human capital. In addition, we assume each input has diminishing marginal returns, that is, $\frac{\partial^2 f_3}{\partial e_2^2} \leq 0$, $\frac{\partial^2 f_3}{\partial c_2^2} \leq 0$, $\frac{\partial^2 f_3}{\partial s_2^2} \leq 0$, and $\frac{\partial^2 f_2}{\partial c_1^2} \leq 0$.

Since no choices are made in the first period, we can restrict our analysis to the decisions made starting in period 2. Thus, the parent solves

⁴While primary school is officially compulsory, in practice many children are in and out of school.

⁵For example, in 1971, 53 percent of villages had a public primary school, in 1991, 73 percent did (Banerjee and Somanathan, 2007), and today almost 100 percent of Indian villages have a primary school (Government of India, 2011).

⁶Because we allow for full flexibility of the human capital production function, we can make this simplification without loss of generality. However, it does change the interpretation of the function slightly, because it represents the household utility of human capital rather than the productive capacity.

$$\max_{s_2 \in [0,1]} \{u_2(c_2) + \beta f_3(e_2, c_2, s_2)\} \text{ s.t. } c_2 \leq w_2(h + (1 - s_2)e_2)$$

Since utility is increasing in consumption, and there is no borrowing or saving in this model, it will always be the case that $c_2 = w_2(h + (1 - s_2)e_2)$. Thus, we can substitute this into the maximization problem to get

$$\max_{s_2 \in [0,1]} \{u_2(w_2(h + (1 - s_2)e_2)) + \beta f_3(e_2, c_2, s_2)\}$$

In order to ensure a globally concave objective function, and thus, a unique optimum, we assume that

$$\left\{ \frac{\partial^2 u_2}{\partial c_2^2} + \beta \frac{\partial^2 f_3}{\partial c_2^2}(e_2, s_2, c_2) \right\} \cdot \beta \frac{\partial^2 f_3}{\partial s_2^2}(e_2, s_2, c_2) > \left\{ \beta \frac{\partial^2 f_3}{\partial c_2 \partial s_2}(e_2, s_2, c_2) \right\}^2, \quad \forall e_2, c_2, s_2$$

This assures that consumption and schooling are neither “too complementary” nor “too substitutable.” That is, the absolute value of the cross partial with respect to consumption and schooling is smaller than that of the second derivatives. Lastly, we assume that

$$\lim_{s_2 \rightarrow 0^+} \frac{\partial f_3}{\partial s_2} = +\infty$$

and

$$\lim_{s_2 \rightarrow 1^-} \frac{\partial f_3}{\partial s_2} = 0$$

These assumptions, while not strictly necessary for analysis of a solution, allow us to ignore corner solutions in which children spend either no time in school or no time on productive work.⁷ We focus on interior solutions because in practice, we find that most children in our data look like they are spending at least some time in school and some time

⁷Because we have assumed that parents supply positive labor, and bounded schooling between 0 and 1, consumption will always be positive.

on productive work.

At an interior optimum, parents equalize the marginal utility consumption from forgoing school now with the marginal benefits of additional human capital later:

$$w_2 e_2 \frac{\partial u_2}{\partial c_2} = \beta \Theta(w_2, e_2, s_2^*, c_2^*)$$

where

$$\Theta(w_2, e_2, s_2^*, c_2^*) = \frac{\partial f_3}{\partial s_2}(e_2, s_2^*, c_2^*) - w_2 e_2 \frac{\partial f_3}{\partial c_2}(e_2, s_2^*, c_2^*)$$

Households tradeoff the marginal benefit of additional utility from consumption with the net long-term benefit of schooling. Note that in an interior solution, since $\frac{\partial u_2}{\partial c_2}$, w_2 , $e_2 > 0$, it must be the case that $\Theta(w_2, e_2, s_2^*, c_2^*) > 0$. That is, at the optimum, schooling is a relatively better technology than working and consuming for turning time into human capital.

We are interested in the effect that wages have on the optimal level of schooling. That is, if wages increase, do children invest more or less in schooling? And, as a result, do overall levels of human capital increase or decrease? In this model, there are two relevant wages—those in early life and those during the child’s school years. We will examine the effect of each of these wages on schooling choices and human capital.

2.1 Effect of School-Aged Wages on Schooling and Human Capital

First, we examine the impact of second period wages, w_2 on the optimal choice of schooling, s_2^* , and the resulting level of human capital, e_3^* . From the first order condition,

$$\frac{\partial s_2^*}{\partial w_2} \propto - \overbrace{e_2 \left(\frac{\partial u_2}{\partial c_2} + \beta \frac{\partial f_3}{\partial c_2} \right)}^{\text{Substitution Effect (-)}} - \overbrace{(h + (1 - s_2^*) e_2) w_2 e_2 \frac{\partial^2 u_2}{\partial c_2^2}}^{\text{Income Effect (+)}} + \overbrace{(h + (1 - s_2^*) e_2) \beta \frac{\partial \Theta}{\partial c_2}}^{\text{Effect of } c_2 \text{ on Net Impact of Schooling}} \quad (1)$$

The effect of school-aged wages on the optimal level of schooling will depend on three things. First, increased wages increase the benefit to working, both through the utility

in period 2, and through the benefit to human capital in period 3 (substitution effect). Second, increased wages will increase consumption, which will decrease the marginal utility of consumption (income effect). Third, the increase in consumption could affect the net impact of schooling. We think it is likely that this term is weakly positive. That is, as consumption increases, schooling becomes relatively better than consumption as a technology for turning time into human capital. If a child is starving, consumption is likely extremely important for the production of human capital. As the level of consumption increases, the benefits of consumption relative to schooling will likely decrease. Thus, even if income effects are small, if schooling becomes relatively more valuable as households get richer, we could still see schooling decrease when wages are higher. Which of these forces will dominate is an empirical question that we address in Section 4.1.

We examine the impact of period 2 wages on period 3 human capital:

$$\frac{d}{dw_2} (f_3(e_2, c_2^*, s_2^*)) = (h + (1 - s_2^*)e_2) \frac{\partial f_3}{\partial c_2} + \Theta \frac{\partial s_2^*}{\partial w_2} \quad (2)$$

The first term in this expression is positive by assumption: it is the mechanical effect of higher wages on consumption which in turn increases human capital. We also know that Θ is positive at any interior optimum, so if increased wages lead to increased schooling, we know that human capital will increase as a result. However, if increased wages decrease the optimal level of schooling, then the effect on human capital will be ambiguous. The sign will depend on whether this behavioral effect of lower investment will offset the mechanical increase in human capital due to consumption.

2.2 Effect of Early Life Wages on Schooling and Human Capital

In this model, the only way that early life wages affect the choice of schooling is through their effect on human capital in period 2. Because increased wages mechanically increase consumption in period 1, and human capital in period 2 is an increasing function of period

1 consumption, increased wages in period 1 will always result in increased human capital in period 2:

$$\frac{d}{dw_1}(e_2) = \frac{\partial f_2}{\partial c_1} \frac{\partial c_1}{\partial w_1} = h \frac{\partial f_2}{\partial c_1} > 0$$

Thus, in order to understand the effect of early life wages on schooling and later-life human capital, it is sufficient to study the effect of period 2 human capital on the optimal level of schooling and on period 3 human capital.

$$\frac{\partial s_2^*}{\partial w_1} = h \frac{\partial f_2}{\partial c_1} \frac{\partial s_2^*}{\partial e_2} \propto \frac{\partial s_2^*}{\partial e_2}$$

From the first order condition, we can derive the effect of period 2 human capital on the optimal choice of schooling:

$$\frac{\partial s_2^*}{\partial e_2} \propto \underbrace{-w_2 \frac{\partial u_2}{\partial c_2}}_{\text{Substitution Effect (-)}} \underbrace{-w_2^2 e_2 (1 - s_2^*) \frac{\partial^2 u_2}{\partial c_2^2}}_{\text{Income Effect (+)}} + \beta \underbrace{\left[\frac{\partial \Theta}{\partial e_2} + w_2 (1 - s_2^*) \frac{\partial \Theta}{\partial c_2} \right]}_{\text{Net impact of additional } e_2 \text{ on } \Theta} \quad (3)$$

Increased period 2 human capital has three effects on the optimal level of schooling. First, increased human capital increases the value of work in the second period (substitution effect). Second, increased human capital leads to higher income, which reduces the marginal utility of consumption (income effect). Third, the net benefit of schooling, $\Theta(w_2, e_2, s_2^*, c_2^*)$, could be affected by the increase in human capital, in two ways. First, if there are “dynamic complementarities” in the sense of Cunha and Heckman (2007), we would expect the return to schooling to increase with early life investments. In addition, since additional early life human capital also increases consumption mechanically, this could also effect the net benefit of schooling even without dynamic complementarities. However, whether these effects will be large enough to overcome the substitution effects is again an empirical question, which we will address in Section 4.2.

We can examine the impact of childhood human capital on adult human capital. Again,

$$e_3^* = f_3(e_2, c_2^*, s_2^*)$$

$$\frac{d}{de_2}(e_3^*) = \frac{\partial f_3}{\partial e_2} + \frac{\partial f_3}{\partial c_2} w_2 (1 - s_2^*) + \Theta \frac{\partial s_2^*}{\partial e_2} \quad (4)$$

Intuitively, the first term can be thought of as the persistence of early life human capital, and is weakly positive by assumption. The second term takes into account the mechanical increase in consumption derived from an increase in early life human capital (through increased wages) and is also positive by assumption. From the third term, we know that Θ is positive at the optimum, so if early life human capital increases schooling, then it will unambiguously increase human capital as well. If not, it is unclear which effect will dominate.

In the following sections, we will empirically estimate $\frac{\partial c_1}{\partial w_1}$, $\frac{\partial s_2^*}{\partial w_2}$, $\frac{\partial s_2^*}{\partial w_1}$, $\frac{d}{dw_1}(e_3^*)$, and $\frac{d}{dw_2}(e_3^*)$.

3 Background and Data

3.1 Cognitive Testing and Schooling Data

Every year since 2005, the NGO Pratham has implemented the Annual Status of Education Report (ASER), a survey on educational achievement of primary school children in India which reaches every rural district in the country.⁸ We have data on children from 2005-2009, giving us a sample size of approximately 2 million rural children. The sample is a representative repeated cross section at the district level. The ASER data is unique in that its sample is extremely large and includes both in and out of school children. Since cognitive tests are usually administered in schools, data on test scores is necessarily limited to the sample of children who are enrolled in school (and present when the test is given). However, ASER tests children ages 5-16, who are currently enrolled, dropped out, or have never enrolled in school. In Table 1 we describe the characteristics of the children in our

⁸This includes over 570 districts, 15,000 villages, 300,000 households and 700,000 children in a given year. For more information on ASER, see <http://www.asercentre.org/ngo-education-india.php?p=ASER+survey>

sample as well as their test scores.

The ASER surveyors ask each child four questions each in math and reading (in their native language). The four math questions are whether the child can recognize numbers 1-9, recognize numbers 10-99, subtract, and divide. The scores are coded as 1 if the child correctly answers the question, and 0 otherwise. In 2006 and 2007, children were also asked two subtraction word problems, which we use as a separate math score (Math word problem). The four literacy questions are whether the child can recognize letters, recognize words, read a paragraph, and read a story. We calculate a “math score” variable, which is the sum of the scores of the four numeracy questions. For example, if a child correctly recognizes numbers between 1-9 and 10-99, and correctly answers the subtraction question, but cannot correctly answer the division question, then that child’s math score would be coded as 3. The “reading score” variable is calculated in exactly the same way. In addition, the survey asks about current enrollment status and grade in school, and in 2008, attendance in the past week.⁹ Table 1 summarizes the means of test scores and the schooling outcomes for children in the ASER sample.

3.2 NSS Data

To examine the impact of rainfall shocks on work and wages, we use the NSS (National Sample Survey) Rounds 60, 61, 62, and 64 of the NSS data which was collected between 2004 and 2008 by the Government of India’s Ministry of Statistics. This is a national labor and employment survey collected at the household level all over India. This dataset gives us measures of employment status as well as wages at the individual level. Given the potential measurement error in the valuation of in-kind wages, we define wages paid in money terms. We use data from all rural households in this survey and merge with our district level rainfall data to explore the relationship between weather shocks, labor force participation, school attendance, and wages.

⁹More information on the ASER survey questions, sampling, and procedures can be found in the ASER data appendix.

3.3 Rainfall Data

We use monthly rainfall data which is collected by the University of Delaware to determine rainfall shock years within districts.¹⁰ The data covers all of India in the period between 1900-2008 and we use data from 1975-2008 in this paper. The data is gridded by longitude and latitude lines, so to match these to districts, we simply use the closest point on the grid to the center of the district, and assign that level of rainfall to the district for each year.

We define a positive shock as yearly rainfall above the 80th percentile and negative shock (drought) as rainfall below 20th percentile within the district. The “positive” and “negative” shocks should not be taken in an absolute sense—we are not comparing districts that are prone to higher rainfall to those that are prone to lower rainfall. These are simply high or low rainfall years for each district within the given time frame. For the analysis, we define “rain shock” as equal to 1 if rainfall is above the 80th percentile, -1 if rainfall is below the 20th percentile, and 0 otherwise. These are similar to the definitions employed in Kaur (2011) and Jayachandran (2006).¹¹ Table A2 shows the percent of districts each year that experience a drought or positive rainfall shock; the variation in rainfall across time and space is quite extensive.

In a data appendix, we explicitly test for serial correlation of rainfall because if droughts this year are correlated with droughts next year, it is difficult to tell the extent to which we are picking up the effects of a single shock or multiple years of rainfall shocks. However, we find no significant evidence of serial correlation across years. In addition, we check for spatial correlation. If there is significant within-district variation in rainfall, our district-level measure of rainfall variation might be missing the true effects for many of the children in our sample. However, we find that this type of very local variation is unlikely to be biasing our results (results available upon request).

¹⁰The data is available at: http://climate.geog.udel.edu/~climate/html_pages/download.html#P2009

¹¹In previous versions of the paper we showed results separately for positive and negative rainfall shocks and using rainfall quintiles and the results are qualitatively similar.

3.4 Rainfall Shocks in India

In rural India, 66.2 percent of males and 81.6 percent of females report agriculture (as cultivators or laborers) as their principal economic activity (Mahajan and Gupta, 2011). Almost 70 percent of the total net area sown in India is rainfed; thus, in this context we would expect rainfall to be an important driver of productivity and wages. While there is plenty of evidence showing droughts adversely affect agricultural output and productivity in India (see for example Rao et al. (1988), Pathania (2007)), we also explore this question empirically using the World Bank India Agriculture and Climate Data set. In Table A1 we show results from regressions of rice, wheat, and jowar yields on rainfall shocks. In drought years, crop yields are significantly lower regardless of the type of crop (and the opposite is true in positive rain shock years).

In Table A1, we measure the effect of rainfall shocks on wages using NSS data.¹² We find that for positive rainfall shocks result in increased wages. In Table A1, we also show that agricultural yields are significantly higher across all types of crops in years with more rainfall, controlling for labor and other inputs. These results give us confidence that rainfall shocks are indeed a productivity, and thus, wage shifter in this context.

4 Empirical Strategy and Results

In Section 2, we outlined a model in which the effects of early life and school-aged wages on human capital was ambiguous. We now estimate these comparative statics using the test score and schooling data from India.

To understand the impact of school-aged wages on schooling and human capital, we estimate the impact of current year rainfall shocks on current levels of schooling and human capital. To determine the effects of early life wages on human capital outcomes, we need to regress current test scores on lagged rainfall since we do not have measures of human capital

¹²While there is extensive literature in economics and other fields both documenting this fact and using it to estimate economic parameters of interest (see for example Jayachandran (2006); Maccini and Yang (2009); Jensen (2000); Kaur (2011)), we also test for the relationship using our data.

for very young children. In both cases, we will rely on the quasi-random nature of negative and positive rainfall shocks within districts as a natural shifter of rural wages. We outline both strategies in detail below.

4.1 Estimating Effect of School-Aged Wages on Schooling and Human Capital

In order to determine the impacts of wages on human capital and schooling ($\frac{\partial s_2^*}{\partial w_2}$ and $\frac{d}{dw_2}(e_3^*)$), we estimate the regression:

$$S_{ijty} = \alpha + \beta_1 \delta_{j,y} + \beta_2 \delta_{j,y-1} + \zeta \theta_{j,t} + \gamma_j + \phi_t + \psi_y + \epsilon_{ijty} \quad (5)$$

where S_{ijty} is the measure of human capital or schooling for student i in district j born in year t and surveyed in year y . As measures of e_3 , we use math and reading test scores, as well as “on track” which is a measure of age-for-grade. We define on track as a binary variable which indicates if a child is in the correct grade for his/her age. The variable is coded 1 if age minus grade is at most six. That is, if an eight year old is in second or third grade, he is coded as on track, but if he is in first grade, he is not. We use self-reported attendance and an indicator of having dropped out of school as two measures of s_2 , schooling in period 2. $\delta_{j,y}$ is rain shock in district j in year y and $\delta_{j,y-1}$ is a lagged rain shock. β_1 is the impact of current year rain shock on the various cognitive test scores and schooling outcomes. We also control for early life rainfall exposure by including $\theta_{j,t}$, a vector of early life rainfall shocks from in utero to age 4. γ_j is a vector of district fixed effects, ϕ_t is a vector of age fixed effects, and ψ_y is a vector of year of survey fixed effects. This specification allows us to compare children who are surveyed in different years from the same district. Since our regressions contain district level fixed effects, the coefficient will not be biased by systematic differences across districts. Standard errors are clustered at the district level.

In Panel A of Table 2 we report the results from Equation 5 estimating the impact of contemporaneous rainfall shocks on test scores and schooling outcomes of children ages 5-

16.¹³ The coefficient on math score is $-.02$, which means that, relative to a positive rainfall year, children tested in a drought year score $.04$ points better (or 1.5 percent) on the math test. The coefficient on math word problem is $-.05$ which means that relative to a positive rainfall year, children in a drought district score 0.1 points more (or 8 percent). While rain shocks this year do not impact reading scores, positive rainfall shocks in the previous year significantly decrease reading scores as well.

Rainfall shocks in the previous year significantly affect both age for grade and dropping out. Children in a positive rainfall shock year are $.4$ percentage points more likely to report having dropped out in the following year, relative to children tested in drought years (this is an increase of 11% from a mean of $.036$). Likewise, children tested in a positive shock year are 2 percentage points less likely to be on track, relative to a drought year. In addition, children who currently experience drought are 4 percentage points more likely to have attended school in the previous week (from a mean of 86 percent) relative to a positive rainfall shock.

In Panels B and C of Table 2, we report these coefficients separately estimated for children aged 5-10 and aged 11-16. Most of the magnitudes are similar in size, although the effect of rainfall on dropouts and being on track appears to be almost entirely driven by older children. Indeed, Figure 1 shows the the coefficient of lagged rain shock on dropping out estimated for each age separately. It appears that experiencing a positive rainfall shock from age 12 onward results in a higher likelihood of dropping out, though the estimates are noisy. This makes sense since this is the period children transition from primary to secondary school and when outside job opportunities during high rainfall years might lure them away from school.

In Table 3 Panel A, we also estimate the impact of rain shocks on children's reported "primary activity" using NSS data to corroborate the ASER attendance results. We find that during positive rainfall shocks, children are 2 percentage points less likely to report attending school and 20 percent more likely to report working relative to a drought year.

¹³We only use ASER rounds 2005-2008 for Table 2 (not the 2009 round) because the rainfall data is only available to 2008 so there is no current measure of rain shock for children in the 2009 ASER round.

In Panels B and C, we report these coefficients separately estimated for children ages 5-10 and ages 11-16. As in the ASER data, the effects are larger for older children. Note that these categories (child primarily attends school or primarily works) are mutually exclusive in the questionnaire, so that any intensive margin changes in work or school attendance are not picked up here. Because of this, it is possible that these results understate the rain dependent substitution between schooling and labor for children.

We find that both schooling and human capital are lower during higher rainfall years when children are over the age of 5.

4.2 Estimating the Effect of Early Life Wages on Schooling and Human Capital

We use a lagged rainfall specification to estimate the effect of early life wages on later schooling ($\frac{\partial s_2^*}{\partial w_1}$) and human capital ($\frac{d}{dw_1}(e_3^*)$). In all specifications, we look at lagged effects of rainfall shocks on current outcomes exploiting cohort variation in rain exposure.¹⁴

To examine the effect of early life wages on human capital and schooling, we estimate the following regression:

$$S_{ijhty} = \alpha + \zeta\theta_{j,t} + \lambda_h + \phi_t + \psi_y + \epsilon_{ijhty} \quad (6)$$

where S_{ijhty} is the measure of human capital or schooling of student i in district j born in year t and surveyed in year y , who is a member of household h . Again we use math and reading scores and “on track” as our measures of e_3 and “never enrolled in school” as a measure of s_2 . $\theta_{j,t}$ is a vector of early life rain shocks from in utero to age 4, λ_h is a vector of household fixed effects, ϕ_t is a vector of age fixed effects, and ψ_y is a vector of year of survey fixed effects. ζ is the vector of coefficients of interest and it is the impact of early life rainfall shocks at each age on human capital outcomes. Comparing children from the

¹⁴In our data, we do not observe exact date of birth, only age at time of survey. We generate year of birth=survey year-current age; but this measure of rainfall at each age will be somewhat noisy. We examine this issue in detail in an online appendix and show that the main results are similar when we correct for measurement error.

same district who were born in different cohorts allows us to use household fixed effects in this regression.¹⁵ Household fixed effects allow us to rule out the possibility that the results are driven by lower ability children showing up more frequently in drought cohorts due to selective migration or fertility. Standard errors are clustered at the district level. We discuss potential selection issues in Section 5 below.

Table 4 presents the main estimates of the effect of early life rainfall on test scores and schooling outcomes. In the first three columns, we examine the effect of rainfall on math test scores, math word problems, and reading test scores. The coefficient on rain shock between the in utero period and age 2 ranges from .006-.02, which implies that for each year of exposure to positive rainfall, children score .012-.04 points higher on these tests relative to drought years, and for each year of exposure to drought, they score .02-.04 points lower relative to a positive shock year. In column 4, we show that drought exposure at every year from the in utero period to age 4 is associated with a higher probability of the child never having enrolled in school. The coefficients range from -.002 to -.003, relative to a mean of .028. In column 5, we show that from the in utero period to age 2, exposure to positive rainfall shocks significantly increases the probability of a child being on track. The coefficients range from .01-.02, from a mean of 0.781. These results are consistent with the idea that both schooling investments and human capital achievement are higher when wages are higher in early life. The coefficients for nearly all variables are much smaller for exposure at ages 3 and 4, which indicates that the “critical period” for income effects might end around age 2.

Additionally, our model predicts that children’s early life consumption should increase with early life wages ($\frac{\partial c_1}{\partial w_1} > 0$) under a wide range of assumptions. We test this prediction

¹⁵If drought exposure is indeed IID, and there are no intervening mechanisms which could affect outcomes, this specification should yield exactly the same results as using district fixed effects, except that it is identified off of households with more than one child. However, it is possible that parents could react to one child’s drought exposure by reallocating resources within the household, either by shifting them toward or away from the affected child. Thus, other children in the household could be affected by their sibling’s drought exposure. Regressions estimated with district fixed effects are qualitatively similar, and available upon request.

in Table 5 using IHDS 2004–2005 data for children ages 1-5.¹⁶ We regress weight for age z-scores (using the 2006 WHO child growth standards for children ages 1-5) on rainfall shocks. We show that children have significantly lower weight for age z-scores in drought years (by .12 standard deviation) and higher weight for age z-scores in positive rainfall shock years. Consistent with our model, we find evidence that early life consumption is higher when rainfall levels are higher.

Though others have examined the impact of early life shocks on health outcomes, wages, and total years of schooling, there is little medium term evidence on human capital directly (i.e. test scores). Our results are similar to Akresh et al. (2010) who also find negative effects of shocks in utero and infancy and Maccini and Yang (2009) who find positive effects of early life rainfall on human capital. However, both of these papers find different effects for different groups and ages. Akresh et al. (2010) find that the most important year is the in utero year while Maccini and Yang (2009) find it is the year after birth (and only for girls). We find largely similar effects for children under three and do not find large differences by gender. Our coefficients suggest that the in utero effects are slightly larger for girls and that girls exposed to droughts are less likely to enrol in school relative to boys, but standard errors in most cases do not allow us to detect significant differences between boys and girls (results by gender are shown in Appendix Tables A6-A9).

Consistent with the literature (Almond and Currie, 2011; Currie and Vogl, 2013), we find that more early life rainfall is associated with more early life consumption, more schooling investment, and higher levels of human capital in later childhood.

4.3 Are there Long-Term Effects of Rainfall Shocks?

We are also interested in the effect of total childhood rainfall shocks experienced on total schooling ($\frac{\partial s_2^*}{\partial w_1}$ and $\frac{\partial s_2^*}{\partial w_2}$). Table 2 indicates that students in districts with positive rainfall

¹⁶The India Human Development Survey (IHDS) is a nationally representative survey of 41,554 households in 1503 villages and 971 urban neighborhoods across India. The data and more information is available online at ihds.umd.edu.

shocks have lower contemporaneous test scores. The results in Table 2 also suggest that there are lagged effects for positive rainfall shocks, perhaps due to the increased propensity to drop out in these years as well. It is possible, however, that this represents simple intertemporal substitution of school time, and that children make up these differences in human capital over time (Jacoby and Skoufias, 1997; Funkhouser, 1999).

To test for this, we use the NSS data on young adults (ages 16-30) and the outcome variable for this specification is total years of schooling. Instead of using only early life exposure, we replace $\theta_{j,t}$ with a vector of rain shocks from in utero to age 16. We include district fixed effects and control for age and sex in this specification.

Table 6 indicates that starting at approximately age 3, in almost every year of life, higher rainfall is associated with lower levels of schooling. The magnitudes are largest between ages 11-13 (a positive rainfall shock at age 12 reduces total years of schooling by approximately .23 years relative to a normal rainfall year). This makes sense, since the transition from primary to secondary school is a common time for students to drop out of school. We graph the coefficients from this regression in Figure 2. The results clearly indicate that the worst time to experience a positive rainfall shock for total years of schooling is in these transition years from primary to secondary. This is already when many children drop out of school as shown in the ASER data and experiencing a positive rainfall shock exacerbates this problem.

We find evidence in this section that the effects of rainfall on schooling and human capital can last into adulthood. Those who experienced higher rainfall on average in later childhood have fewer total years of schooling as adults. Thus, it is likely that students are not substituting across time, but that these changes in human capital represent real, lasting differences.

4.4 Discussion of Results and Model

In the empirical analysis, we find that higher wages when a child is of school age decrease both the level of human capital and the investment in human capital. That is, $\frac{d}{dw_2}(e_3^*) < 0$

and $\frac{\partial s_2^*}{\partial w_2} < 0$. From Equation 1, $\frac{\partial s_2^*}{\partial w_2} < 0 \implies$

$$e_2 \left(\frac{\partial u_2}{\partial c_2} + \beta \frac{\partial f_3}{\partial c_2} \right) > (h + (1 - s_2^*) e_2) w_2 e_2 \frac{\partial^2 u_2}{\partial c_2^2} + (h + (1 - s_2^*) e_2) \beta \frac{\partial \Theta}{\partial c_2} \quad (7)$$

That is, the substitution effect dominates: the combined benefit of additional consumption, through utility in period 2 and increased human capital in period 3, outweighs both the income effect and the increased benefit of schooling as consumption increases.

From Equation 2,

$$\frac{d}{dw_2} (e_3^*) < 0 \implies \frac{\partial f_3}{\partial s_2} > \left(\frac{w_2 e_2 \frac{\partial s_2^*}{\partial w_2} - (h(1 - s_2^*) e_2)}{\frac{\partial s_2^*}{w_2}} \right) \frac{\partial f_3}{\partial c_2}$$

This indicates that the effect of schooling on human capital is larger, at least at the optimal level of consumption and schooling in our empirical setting, than the impact of the increased consumption from both the mechanical effect of higher wages, and the behavioral response of increased child labor. In other words, even though incomes and consumption are increasing, human capital is decreasing because of decreased schooling.

Secondly, we find that early life wages increase both investments in schooling and the level of human capital, $\frac{\partial s_2^*}{\partial w_1} > 0$ and $\frac{d}{dw_1} (e_3^*) > 0$, respectively. From Equation 3,

$$\frac{\partial s_2^*}{\partial w_1} > 0 \implies w_2 \frac{\partial u_2}{\partial c_2} < w_2^2 e_2 (1 - s_2^*) \frac{\partial^2 u_2}{\partial c_2^2} + \beta \left[\frac{\partial \Theta}{\partial e_2} + w_2 (1 - s_2^*) \frac{\partial \Theta}{\partial c_2} \right] \quad (8)$$

That is, the income effect from higher wages in period 2 is dominated by the income effect combined with the differential returns to schooling caused by increased period 2 human capital and consumption. In addition, the empirical analysis suggests that $\frac{d}{dw_1} (e_3^*) > 0$ which is reassuring, since from Equation 4, if $\frac{\partial s_2^*}{\partial e_2} > 0$, it must be the case that $\frac{d}{dw_1} (e_3^*) > 0$.

In addition, combining and rearranging inequalities 7 and 8 yields the following inequality:¹⁷

¹⁷See Mathematical Appendix for derivation.

$$\beta \frac{\partial \Theta}{\partial e_2} > w_2 \left[\frac{h}{(h + (1 - s_2^*) e_2)} \frac{\partial u_2}{\partial c_2} - \frac{(1 - s_2^*) e_2}{(h + (1 - s_2^*) e_2)} \beta \frac{\partial f_3}{\partial c_2} \right]$$

That is, the derivative of the net benefit of schooling with respect to period 2 human capital (or the net dynamic complementarities) is bounded below by the wage times the expression in brackets. The first term in the expression is the fraction of household income earned by the parent $\left(\frac{h}{h + (1 - s_2^*) e_2} \right)$, which in this context is likely close to one times the marginal utility from consumption, which is positive by assumption. The second term is the fraction of household income earned by the child $\left(\frac{(1 - s_2^*) e_2}{h + (1 - s_2^*) e_2} \right)$ times the discounted marginal effect of additional consumption in period 2 on later-life human capital $(\beta \frac{\partial f_3}{\partial c_2})$.

Without additional assumptions on $\beta \frac{\partial f_3}{\partial c_2}$, we cannot say whether this expression will be positive. We do know that if $\frac{\partial f_3}{\partial c_2}$ is close to zero (which is consistent with our results that schooling effects dominate consumption effects), then the expression in brackets will be positive. This is also consistent with substantial evidence that both schooling and consumption early in life effect human capital, but little evidence of contemporaneous consumption having similar effects. If, however, $\frac{\partial f_3}{\partial c_2}$ is not small (relative to $\frac{\partial u_2}{\partial c_2}$), then the expression in brackets will be positive if the fraction of income earned by the child is small enough. In this setting, though children do contribute to household income through labor, their contribution is almost always significantly less than their adult counterparts. If either of these conditions holds, our findings can be seen as evidence for dynamic complementarities in the human capital production function.

5 Alternative Explanations

Since we use rainfall shocks as a proxy for wages in this paper, other aspects of abnormally high or low rainfall that affect human capital could be a threat to our identification. We discuss three such possibilities in this section. First, we examine whether direct disease mechanisms, caused by excess water from high rainfall years, could cause children to become

sick and attend school less. Second, we explore whether school lunches, now a common phenomenon in India, could be driving children to attend school more during drought years. Third, we examine whether the rain shocks could affect the outside options for teachers, affecting the quality of schooling directly. Each of these explanations could, in theory, bias our estimated coefficients from Table 3 upward. Below, we examine each of these explanations in turn, and find evidence in each instance that they are unlikely to be driving our results. We then explore how selective migration, mortality, or fertility responses may impact our main results.

5.1 Healthier Children

If less rainfall leads to lower endemicity of particular diseases, this could cause children to attend school more during drought years for reasons unrelated to their outside option. Two common diseases for children in India for which there has been a link discussed between weather patterns and disease rates are diarrhea and malaria. Rainfall variability as manifest through more frequent flooding has been linked to increases in the prevalence of diarrhea in studies in India, Bangladesh, Mozambique, and even in the USA (Curriero et al., 2001; IPCC, 2007). However, other studies have shown that shortage of rainfall in the dry season increases the prevalence of diarrhea (see for example Sub-Saharan Africa (Bandyopadhyay et al., 2012)). In fact, heavy rainfall events decreased diarrhea incidence following wet periods in Ecuador (Carlton et al., 2013).

The evidence for malaria is similarly controversial. While we generally think more rain is associated with higher rates of malaria, there is evidence that droughts result in river margins retreating leaving numerous pools suitable for vector breeding exacerbating the spread of malaria (Haque et al., 2010). Nevertheless, since malaria prevalence varies considerably by region, we can test for the possibility that differences in malaria infections during drought years might explain the test score results. In Table A11 we re-estimate our contemporaneous shock regressions including an interaction of rainfall shock with an indicator for whether the

district is in a high-malaria state (i.e. Orissa, Chhattisgarh, West Bengal, Jharkhand, and Karnataka (Kumar et al., 2007)). The results in Table A11 indicate that there is no additional statistically significant effect of rainfall shocks in malaria states, and thus it is unlikely this channel is driving the contemporaneous test score results.

We test for the overall health impacts of rainfall shocks on children ages 5-16 using the IHDS data in Table A10. The concern is that for whatever reason, children are healthier during drought years which results in them attending school more and doing better on their tests. In column 1 we regress the number of days ill in the past month due to diarrhea, cough, or fever. The results indicate that children are actually healthier in positive rainfall shock areas. Children spend 0.52 fewer days (or 10 percent) being ill. In column 2, we regress ln health expenditures (doctors, medicine, hospital and transportation) on rainfall shocks. Again the results suggest that children are healthier in positive rainfall shock years. Medical health expenditures are 44 percent lower in positive rainfall shock years, relative to drought. This is despite the fact that incomes are higher in positive shock years and lower in negative shock years. Therefore, we can conclude that children do not appear to be healthier in drought years.¹⁸

5.2 School Lunches

In November 2001, in a landmark reform, the Supreme Court of India directed the Government of India to provide cooked midday meals in all government primary schools (Singh et al., forthcoming). Since that time, many schools have begun lunch programs, but compliance is still under 100 percent. One concern is that schools might be more likely to serve lunches during droughts and that parents respond to this by sending their children to school for the meals. We test whether schools are more likely to serve lunches during droughts using the

¹⁸We cannot rule out the case that children work more in high rainfall years because they are healthier. This could be the case, for example, if health increased the return to working more than it increased the return to schooling. However, most empirical evidence on this topic finds that increasing health increases schooling investment, particularly in the developing world (Miguel and Kremer, 2004; Jayachandran and Lleras-Muney, 2008; Bleakley, 2007).

ASER School Survey data, and do not find any evidence of this. In fact, column 2 of Table A12 indicates that lunches are more likely to be provided in positive rainfall shock years. This makes sense since these are the years everyone is better off so districts or schools may have more resources to provide lunches.

5.3 Teacher Attendance

Tables A1 and 3 illustrate that employment and wages are affected by rainfall shocks. Thus, as the outside option for students and parents increases in value, so does the outside option for teachers. It is possible that the effects of rainfall shocks on test scores, and even on student absence and dropout rates, could be the result of teacher absences. We think this is unlikely in the context of India, because while absence rates for teachers are high overall (Chaudhury et al., 2006), teachers are well-educated and well-paid workers, and the wages that are most affected by rainfall shocks are those for agricultural laborers who earn very little. The additional wage income available during good years for day labor such as weeding and harvesting is small relative to teacher's salaries.¹⁹

In column 1 of Table A12 we show the impact of rainfall shocks on teacher absence rates recorded by surveyors in the ASER School Survey. The results indicate that teachers are less likely to be absent from school in positive rainfall shock years. Therefore, teacher absence is not likely to be the driver of the test score results in Table 2.²⁰

5.4 Selective Migration in Contemporaneous Regressions

The primary selection concern for our main results in Table 2 is that ASER is sampling a different set of children in districts experiencing higher than average rainfall relative to districts experiencing lower rainfall. Specifically, if higher ability children are systematically

¹⁹Indeed, wages in the educational sector can be as much as 10 times higher than wages in the agricultural sector (NSS 2005 data).

²⁰It is important to note that the school lunch and teacher absence results presented in Table A12 are suggestive because the schools sampled in the ASER School Survey (unlike the households) are not a representative, random sample of schools in the district.

less likely to be surveyed when rainfall is highest, this could bias our results upward. Fortunately, ASER has a procedure designed to reduce sample selection as much as possible. Enumerators are instructed to visit a random sample of households only when children are likely to be at home; they must go on Sundays when children are not in school and no one works. If all children are not home on the first visit, they are instructed to revisit once they are done surveying the other households (ASER, 2010).

This would not alleviate the issue if these students are leaving their districts permanently when rainfall is particularly high (or low). However, migration rates in rural India are extremely low. For example, Topalova (2005) using data from the National Sample Surveys finds that only 3.6 percent of the rural population in 1999-2000 reported changing districts in the previous 10 years. Munshi and Rosenzweig (2009) using the Rural Economic Development Survey also conclude that rural emigration rates are low. Indian Census data from 2001 shows that the inter-district rural migration rate for all ages is .078. However, the rate drops to .02 when we look at children ages 5-14. Interestingly, the main reason for migration for females is marriage (65 percent of female migrants) and work/employment for men (37.6 percent of male migrants).

In Table A14 using NSS data from round 55 (1999-2000) we regress whether members of households have stayed in the same village for the past 6 months or more on rainfall shocks. This allows us to test whether individuals are responding to positive or negative rainfall shocks with temporary migration. In columns 2 and 4 we restrict our samples to children ages 5-16, the same ages as the ASER sample. The results are very much in line with the census data. Firstly, only about 2 percent of rural households report to having moved in the last 6 months (or more). However, it does not appear that migration decisions are being driven by rainfall shocks. The magnitudes of the coefficients are close to 0 and the results are not statistically significant.

We can take these coefficients seriously and bound our results in the spirit of Manski (1990). We assume the worst case scenario for our hypothesis: that all excess movement into

drought districts is high-scoring children, and all movement into positive shock districts is from low-scoring children. Essentially, we want to ask whether there is any way the amount of rain-responsive migration could be driving our results. In simulations, we find that even under the starkest assumptions (that all children who move into a drought district scored 4 on all tests, and all children who moved into positive shock districts scored 0 on all tests), our results are remarkably unchanged. Ninety-five percent of the simulation results changed the coefficients for math score, math word score, and reading score by less than .0007, .0003, and .0006 respectively. Migration rates, particularly short-term migration rates among young children, are simply too small to explain our results.

Lastly, we are encouraged by the fact that the NSS results tell the same story as the ASER test score results. For the NSS survey, children do not need to be at home to take tests or answer questions; one family member answers basic questions (such as working status and school enrollment) for the entire household. In addition, in the long-term analysis using the NSS data, people who experienced higher rainfall at particular ages have lower overall schooling, which is consistent with the dropout rates we observe in the ASER sample.

5.5 Selective Migration in Early Life Regressions

The sort of selective migration that could bias our early life regressions in Table 4 is somewhat different. Even if migration patterns are driven by rainfall patterns, as long as these migration patterns are not age specific, then they would not bias our estimated coefficients. In the context of our early life results, this is reasonable. For instance, even if children exposed to drought conditions under the age of two are more likely to move (and those who move are positively selected biasing our results upward), they would likely move with their whole family including older and younger siblings. Thus, each “treatment” child would likely travel with several “control” children. In our main specification in Table 4, we use household fixed effects which means that the child is only compared to the other children in his household mitigating any concerns that household migration could be driving our results.

In the long term results in Table 6, our main finding is that rainfall shocks around the ages of 11-15 matter for later life outcomes. In the NSS and the ASER data, we assume that the district in which an individual is surveyed is the district in which he spent those years. As stated above, cross district migration is not terribly common in India, and to the extent that it is orthogonal to drought exposure in childhood, it will simply attenuate our results. However, if children are systematically moving out of districts in which there is low rainfall when they are leaving school, this could bias our results. However, again to the extent that these migrants are positively selected this will bias our results downward, since high rainfall at puberty is negatively associated with later life outcomes.

It is also important to remember that rainfall shocks are defined as the top and bottom quintile of rainfall, respectively. The average child will experience approximately 2 to 4 rainfall shocks by this definition over the course of his childhood, and it is unlikely that he is leaving the district in response to relatively small productivity fluctuations.

5.6 Selective Fertility and Mortality

In the early life analysis, one potential concern with trying to understand the effect of drought on cognitive development is that we only observe children who survive and make it into the sample; if drought exposure increases infant and early childhood mortality, it could affect the composition of our sample in “control” and “treatment” years. This selection would most likely bias our results downward; since these are the children who survived, they are positively selected and probably do better on health and educational outcomes relative to the children who died off. Therefore, we are less concerned about bias from selective mortality.

However, another potential concern with the early life results could be if women are delaying or changing fertility patterns in response to droughts. For example, mothers may choose to wait out a drought year before having a child. If droughts are in fact impacting fertility decisions, the empirical results could be biased upward if the children being born in drought years are negatively selected.

Since our dataset includes only children ages 5-16, both of these selection effects would show up as smaller cohort sizes observed for treatment cohorts (assuming that most of the selective mortality happens before age 3). Unfortunately, population by district is only available every 10 years from census data. Therefore we investigate the issue of selective fertility for individuals born in 1991 or 2001 (since that is when census data is available). We regress the ln number of children in each cohort by district on measures of drought and ln population by district in Table A13. In column 3 instead of total population, we use female population ages 15-49 from the 2001 Census since this is the relevant childbearing population. Given we are not exactly sure when mothers and fathers make decisions about when to conceive, we investigate the period 5 years prior to birth.

Table A13 reports the results of these OLS regressions for 1991 and 2001. Most of the coefficients are small, and none are statistically significant in 1991. In columns 2-3, drought in $t-4$ is significantly (and positively) correlated with number of births. However, none of the other coefficients are statistically significant. These data do not suggest that there is a systematic difference in the size of treated cohorts, and thus selective fertility and mortality are unlikely to be driving our results. Recall also that these are not necessarily severe droughts in that they are defined as rainfall below 20th percentile within the district.

Another piece of evidence which points against selective fertility (and selective migration) are the household fixed effects results of Table 4. If either of these mechanisms is driving the results, then within household variation in drought exposure should not affect cognitive test scores. This story relies on between household variation—i.e. that “good” households are acting differently with respect to droughts compared to “bad” households. That is, if “good households” are leaving the area after droughts, or delaying their fertility when there are droughts, then our sample of exposed children would be more heavily weighted toward “bad households” which could bias our results upward. However, the results with and without household fixed effects are extremely similar (results without household fixed effects that include district fixed effects are available upon request), which leads us to conclude that this

type of selection is unlikely to be biasing the estimates.

6 Conclusion

In this paper we estimate the effect of wages on human capital investment using test scores, schooling outcomes, and labor market data from rural India. We show that positive productivity shocks cause lower school enrollment and attendance, and lower overall test scores. We argue that this is due to children substituting from human capital producing activities to outside work or home production when wages are high, using evidence from the NSS labor market survey on children's reported activities.

The estimates of the effect of early life wages on human capital show that early life positive rainfall shocks positively impact both schooling and human capital. Children exposed to higher rainfall in early life score significantly higher on math and reading tests and are less likely to be behind in school or to never have enrolled. A 2% increase in wages increases current test scores for children who experienced a positive rainfall shock in utero to age 2 by about 1.3% of a standard deviation. According to our model, this is evidence of dynamic complementarities in the human capital production function: the early life investments in these children (due to increased consumption) increase not just the level of human capital but also the return to additional human capital investments.

The estimates of the effect of school-aged wages on human capital suggest that going from regular rainfall to a positive rainfall shock increases wages by 2% and decreases math test scores by 2-5% of a standard deviation. This is similar in magnitude to Dahl and Lochner (2012), who show that an increase in household income of \$1000 in the United States increases test scores by 6% of a standard deviation. In addition, our results imply that a wage increase of this size decreases school attendance by 2 percentage points, and decreases the probability that a child is enrolled in school by 1 percentage point. This implies that a positive rainfall shock increases the urban-rural enrollment gap by 15% for 5 to 16 year olds.

It is important to note that our model assumes that schooling has no direct costs, and that there is sufficient scope for substitution from schoolwork to productive work either in the home or in the labor market. In particular, school fees together with liquidity constraints could cause substitution away from schooling during lower wage years even if the assumptions of our strictest model hold. These assumptions are reasonable in India, but may differ in other developing country settings.

The results indicate that opportunity costs of human capital investment matter even for young children, and that higher wages for low education jobs could have the counterintuitive effect of lowering human capital investments in children. These findings are consistent with a growing literature about the effect of price changes on time-intensive investments in children more generally (Cascio and Narayan, 2015; Charles et al., 2015; Atkin, 2012; Miller and Urdinola, 2010). This research could inform policy decisions about poverty alleviation programs. Workfare programs with guaranteed wages such as NREGA in India have become a popular means of redistribution as they provide aid to the poor along with corresponding work incentives. However, workfare programs affect not only overall income, but also the prevailing wage and time cost of family members. Shah and Steinberg (2015) show that NREGA decreases human capital investment especially for adolescents. Lump sum grants or conditional cash transfers might be better options in this context.

Though these results focus on productivity fluctuations rather than steady growth, they indicate that the reaction to wage growth in low income areas could be to decrease investment in human capital which could be detrimental to long term growth and poverty reduction. If poor countries want to increase school enrollment and attendance, they should not only consider fees and tuition, but the opportunity cost of attendance in terms of wages as well.

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Table 1: Summary Statistics

ASER Summary Statistics (Ages 5-16)			
	Mean	Std. Dev.	Observations
Age	10.16	3.13	2,405,642
Math Score	2.62	1.31	2,104,110
Math Word Problem	1.26	.919	843,827
Reading Score	2.70	1.40	2,115,547
Dropped Out	.036	.188	2,193,040
On Track	.778	.415	1,919,939
Attendance	.863	.215	467,606
Never Enrolled	.028	.164	2,405,642
Rainfall Summary Statistics			
Rain Shock Current Year	.148	.631	2,193,040
Rain Shock Previous Year	.093	.631	2,193,040
Rain Shock in Utero	-.011	.572	2,405,642
Rain Shock at Age 1	-.024	.566	2,405,642
Rain Shock at Age 2	-.047	.558	2,405,642
Rain Shock at Age 3	-.058	.558	2,405,642
Rain Shock at Age 4	-.068	.561	2,405,642
NSS Sample			
Works (Ages 5–16)	.053	.224	305,065
Attends School (Ages 5–16)	.795	.403	303,244
ln Wages	5.85	0.91	167,041
Total Years of School (Ages 16–30)	6.21	4.92	306,925
Total Droughts (Ages -1–16)	3.25	1.12	306,925
Total Positive Shocks (Ages -1–16)	3.59	1.23	306,925

Notes: This table shows summary statistics from the ASER, NSS, and rainfall data.

Table 2: Effect of Contemporaneous Rainfall Shocks on Human Capital

	<i>Dependent Variable:</i>					
	Math Score	Math Word Problem	Read Score	Dropped Out	On Track	Attendance
Panel A: Ages 5-16						
Rain Shock Current Year	-0.02 (.01)*	-0.05 (.02)***	.002 (.01)	.0002 (.0008)	.002 (.002)	-.02 (.006)***
Rain Shock Previous Year	-.02 (.01)	-.04 (.02)*	-.02 (.01)*	.002 (.0009)**	-.01 (.003)***	
Observations	2,104,110	843,827	2,115,547	2,193,040	1,919,939	467,606
Mean Dependent Variable	2.62	1.26	2.70	.036	.778	.863
Panel B: Ages 5-10						
Rain Shock Current Year	-.02 (.01)	-.07 (.03)***	-.001 (.01)	.0006 (.0004)	.006 (.002)**	-.02 (.006)***
Rain Shock Previous Year	-.01 (.01)	-.02 (.03)	-.02 (.01)	.0008 (.0004)*	-.006 (.003)**	
Observations	1,154,292	383,271	1,162,482	1,189,704	914,129	254,770
Mean Dependent Variable	2.06	.785	2.08	.009	.877	.843
Panel C: Ages 11-16						
Rain Shock Current Year	-.01 (.01)	-.04 (.02)**	.005 (.009)	-.0004 (.001)	-.001 (.003)	-.014 (.006)**
Rain Shock Previous Year	-.02 (.01)*	-.05 (.02)***	-.03 (.01)**	.004 (.002)**	-.02 (.004)***	
Observations	949,818	460,556	953,065	1,003,336	1,005,810	212,836
Mean Dependent Variable	3.31	1.65	3.46	.070	.688	.887

Source: Test Score Data from ASER 2005-2008. Rainfall Data from University of Delaware.

Notes: This table shows estimates of β_1 and β_2 from equation (5) ($\frac{\partial s_2^*}{\partial w_2}$ and $\frac{d}{dw_2}(e_3^*)$). “Math Score” and “Read Score” range from 0-4. “Math Word Problem” ranges from 0-2 and was only available in 2006 and 2007. “On Track” is equal to one if age minus grade is at least six, and zero otherwise. All regressions also control for in utero to age 4 rainfall shocks. Columns 1-5 contain fixed effects for district, year and age. Since attendance is only observed in 2008, column 6 contains fixed effects for state and age. Panel A includes entire ASER sample ages 5-16 years old, Panel B restricts to ages 5-10; and Panel C to ages 11-16. 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 Contemporaneous Rain Shocks on Schooling and Child Labor

	<i>Dependent Variable:</i>	
	<i>Attends School</i>	<i>Works</i>
Panel A: Ages 5-16		
Rain Shock Current Year	-.01 (.003)***	.005 (.001)***
Rain Shock Previous Year	-.004 (.003)	.001 (.001)
Observations	297,470	299,271
Mean Dependent Variable	.795	.053
Panel B: Ages 5-10		
Rain Shock Current Year	-.005 (.004)	.002 (.0006)***
Rain Shock Previous Year	-.002 (.004)	.001 (.0008)
Observations	154,291	155,274
Mean Dependent Variable	.821	.007
Panel C: Ages 11-16		
Rain Shock Current Year	-.02 (.003)***	.008 (.002)***
Rain Shock Previous Year	-.008 (.003)**	.002 (.002)
Observations	143,179	143,997
Mean Dependent Variable	.766	.103

Source: Attends school and child labor from rounds 60, 61, 62, and 64 of NSS. Rainfall data from University of Delaware.

Notes: This table shows estimates of β_1 and β_2 from equation (5) ($\frac{\partial s_2^*}{\partial w_2}$). The coefficients represent the effect of rain shocks on a dummy variable for whether primary activity is reported as school attendance (column 1) or working (column 2). Panel A restricts the sample to children ages 5-16, Panel B to ages 5-10; and Panel C to ages 11-16. All regressions contain district fixed effects and control for age and sex. All columns contain controls for early life rainfall shock exposure (in utero-age 4). Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 4: Effect of Early Life Rainfall Shocks on Human Capital

	<i>Dependent Variable:</i>				
	Math Score	Math Word Problem	Read Score	Never Enrolled	On Track
Rain Shock In Utero	.01 (.004)***	.006 (.004)	.01 (.004)***	-.002 (.0004)***	.02 (.002)***
Rain Shock Year of Birth	.01 (.004)***	.009 (.004)**	.01 (.004)**	-.002 (.0004)***	.02 (.002)***
Rain Shock at Age 1	.01 (.004)***	.02 (.005)***	.01 (.004)***	-.003 (.0004)***	.02 (.002)***
Rain Shock at Age 2	.01 (.004)**	.02 (.004)***	.01 (.004)***	-.003 (.0004)***	.01 (.002)***
Rain Shock at Age 3	.001 (.004)	.008 (.005)*	.007 (.004)	-.002 (.0004)***	.003 (.002)
Rain Shock at Age 4	.002 (.004)	-.008 (.004)*	.01 (.005)***	-.002 (.0004)***	.005 (.002)***
Observations	2,350,976	843,827	2,362,940	2,405,642	2,100,717
Mean Dependent Variable	2.62	1.26	2.71	.028	.781

Source: Test Score Data from ASER 2005-2009. Rainfall Data from University of Delaware.

Notes: This table shows estimates of ζ from equation (6), the effect of early life rainfall shocks on current test scores and schooling outcomes ($\frac{\partial s_2^*}{\partial w_1}$ and $\frac{d}{dw_1}(e_3^*)$). “Math Score” and “Read Score” range from 0-4. “Math Word Problem” ranges from 0-2 and was only asked in 2006 and 2007. “On Track” is equal to one if age minus grade is at least six, and zero otherwise. All regressions contain fixed effects for household, year and age. 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 Rainfall Shocks on Child Weight

	Weight for age z-score
Rain Shock Current Year	.12 (.05)**
Rain Shock Previous Year	.22 (.06)***
Observations	15,307
Mean Dependent Variable	-1.516

Source: Data on child weight from IDHS in 2004-2005. Rainfall Data from University of Delaware.

Notes: This table shows estimates of the effect of rainfall shocks on weight for age z-scores for children ages 1–5 (or $\frac{\partial c_1}{\partial w_1}$). These are anthropometric z-scores using the 2006 WHO child growth standards. The regression contains age, year, and state 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 6: Effect of Rain Shocks on Total Schooling

<i>Dependent Variable:</i>	Years of Education (Ages 16-30)
In Utero Rain Shock	.006 (.02)
Rain Shock in Year of Birth	.001 (.02)
Rain Shock at Age 1	-.05 (.02)**
Rain Shock at Age 2	-.03 (.03)
Rain Shock at Age 3	-.11 (.03)***
Rain Shock at Age 4	-.09 (.03)***
Rain Shock at Age 5	-.10 (.03)***
Rain Shock at Age 6	-.06 (.03)**
Rain Shock at Age 7	-.02 (.03)
Rain Shock at Age 8	-.05 (.03)*
Rain Shock at Age 9	-.09 (.03)***
Rain Shock at Age 10	-.11 (.03)***
Rain Shock at Age 11	-.27 (.03)***
Rain Shock at Age 12	-.23 (.03)***
Rain Shock at Age 13	-.27 (.03)***
Rain Shock at Age 14	-.08 (.03)***
Rain Shock at Age 15	-.13 (.02)***
Rain Shock at Age 16	-.09 (.03)***
Mean Dependent Variable	6.04
Observations	306,925

Source: Years of schooling from rounds 60, 61, 62, and 64 of the NSS. Rainfall data from University of Delaware.

Notes: This table shows estimates of $\frac{\partial s_2^*}{\partial w_1}$ and $\frac{\partial s_2^*}{\partial w_2}$, the effect of childhood rain shocks on total years of schooling using data for individuals 16-30. The regressions contain district fixed effects and control for age and sex. Standard errors, clustered at the district level, are reported in parentheses. *** indicates significance at 1% level, ** at 5% level, * at 10% level.

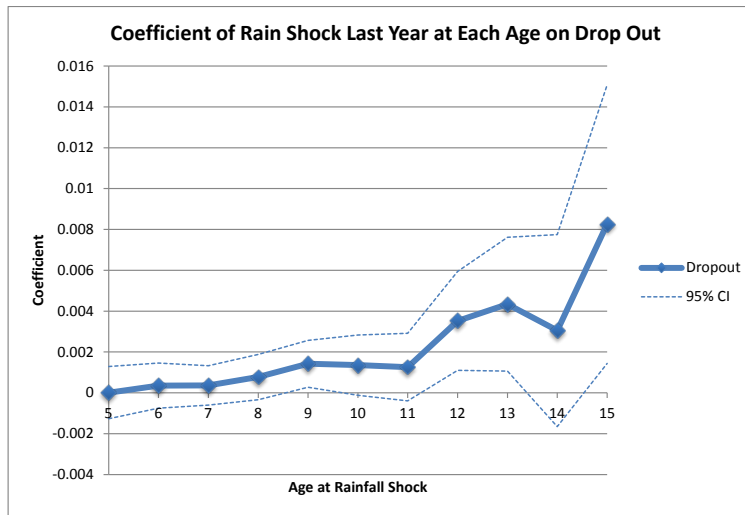


Figure 1: Effect of Rainfall Shocks Last Year on Current Test Scores

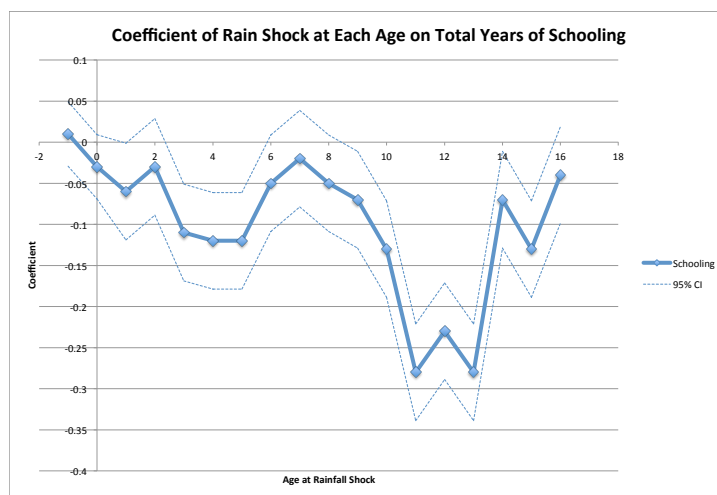


Figure 2: Effect of Rainfall Shocks on Total Years of Schooling

A Appendix Tables

Table A1: Rainfall shocks, Wages and Crop Yields

	<i>Dependent Variable:</i>							
	Rice		Wheat		Jowar		ln Wages	
Rain Shock Current Year	.06 (.02)**	.08 (.02)***	.002 (.01)	.05 (.008)***	.01 (.01)	.02 (.009)**	.02 (.009)*	
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	
District fixed effects	Y	Y	Y	Y	Y	Y	Y	
Controls	Y	N	Y	N	Y	N	Y	
Observations	7161	8401	6680	8401	6265	7409	167,017	
Mean Dependent Variable	1.51	1.51	.856	.856	.589	.589	5.85	

Source: Data on crop yields and inputs is from World Bank India Agriculture and Climate Data set which has agricultural yield (revenues per acre) data from 1975-1987. Wages data from rounds 60, 61, 62, and 64 of NSS. Rainfall data from University of Delaware.

Notes: This table shows results from a regression of crop yields and wages on rain shocks. For columns 1-6, an observation is a district-year and controls are measures of inputs used in production: labor, bullocks, fertilizer, and machinery, as well as 3-year average yield. For column 7, controls are age and sex. Standard errors are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A2: Percent of Droughts and Positive Rainfall Shocks by Year

Year	% Top Quartile Rainfall	% Bottom Quartile Rainfall
1975	.35	.03
1976	.16	.17
1977	.29	.09
1978	.29	.14
1979	.03	.46
1980	.13	.22
1981	.11	.15
1982	.06	.30
1983	.26	.08
1984	.26	.17
1985	.26	.16
1986	.12	.26
1987	.24	.35
1988	.44	.05
1989	.13	.15
1990	.43	.02
1991	.11	.19
1992	.01	.45
1993	.14	.15
1994	.29	.05
1995	.11	.13
1996	.11	.19
1997	.12	.15
1998	.20	.03
1999	.07	.22
2000	.03	.22
2001	.04	.14
2002	.02	.42
2003	.08	.14
2004	.06	.24
2005	.19	.17
2006	.20	.30
2007	.25	.04
2008	.29	.05

Source: Rainfall data from the University of Delaware.

Notes: This table shows the percent of districts each year that experience a drought and positive rainfall shock.

Table A3: Effect of Contemporaneous Rainfall Shocks on Human Capital (Ordered Logit)

	<i>Dependent Variable:</i>		
	Math Score	Math Word Problem	Read Score
Rain Shock Current Year	-.03 (.02)	-.15 (.07)**	-.002 (.02)
Rain Shock Previous Year	-.03 (.02)	-.15 (.08)**	-.04 (.02)*
Observations	2,109,162	843,827	2,120,708

Source: Test Score Data from ASER 2005-2009. Rainfall Data from University of Delaware.

Notes: This table shows ordered logit estimates of the effect of rainfall shocks on current test scores using the ASER data for all children ages 5-16 (or β_1 and β_2 from equation (5)). “Math Score” and “Read Score” range from 0-4. “Math Word Problem” ranges from 0-2 and is only available in 2006 and 2007. All regressions contain fixed effects for district, year and age. All columns contain controls for early life rainfall shock exposure (in utero-age 4). Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A4: Effect of Contemporaneous Rainfall Shocks on Human Capital

	<i>Dependent Variable:</i>					
	Math Score	Math Word Problem	Read Score	Dropped Out	On Track	Attendance
Panel A: Ages 5-16						
Rain Shock Current Year	-.02 (.01)*	-.05 (.02)***	.002 (.01)	.0002 (.0008)	.002 (.002)	-.02 (.006)***
Rain Shock Previous Year	-.02 (.01)	-.04 (.02)*	-.02 (.01)*	.002 (.0009)**	-.01 (.003)***	
Rain Shock In Utero	-.004 (.003)	.005 (.004)	-.01 (.004)***	.0004 (.0006)	.002 (.002)	.003 (.001)*
Rain Shock Year of Birth	.004 (.004)	.004 (.004)	-.006 (.005)	-.002 (.0006)***	.01 (.002)***	.005 (.002)***
Rain shock at Age 1	.01 (.004)***	.01 (.004)***	.005 (.004)	-.002 (.0006)***	.02 (.002)***	.005 (.002)***
Rain shock at Age 2	.003 (.004)	.02 (.004)***	-.001 (.005)	-.0000344 (.0006)	.01 (.002)***	.006 (.002)***
Rain shock at Age 3	-.005 (.004)	.006 (.004)	.002 (.004)	.001 (.0006)	.004 (.002)**	.008 (.002)***
Rain shock at Age 4	-.007 (.003)**	-.01 (.004)***	-.002 (.004)	-.0007 (.0006)	.004 (.002)***	.004 (.002)**
Observations	2,104,110	843,827	2,115,547	2,193,040	1,919,939	467,606
Mean Dependent Variable	2.62	1.26	2.70	.036	.778	.863
Panel B: Ages 5-10						
Rain Shock Current Year	-.02 (.01)	-.07 (.03)***	-.001 (.01)	.0006 (.0004)	.006 (.002)**	-.02 (.006)***
Rain Shock Previous Year	-.01 (.01)	-.02 (.03)	-.02 (.01)	.0008 (.0004)*	-.006 (.003)**	
Rain Shock In Utero	.009 (.005)*	.01 (.006)*	.0006 (.006)	.0002 (.0003)	.01 (.002)***	-.002 (.003)
Rain Shock Year of Birth	.02 (.006)***	.03 (.007)***	.006 (.007)	-.0003 (.0003)	.01 (.002)***	.002 (.003)
Rain Shock at Age 1	.01 (.006)	.02 (.007)***	.02 (.007)**	-.0004 (.0003)	.01 (.003)***	.0000157 (.003)
Rain Shock at Age 2	-.01 (.006)**	-.004 (.007)	-.005 (.007)	-.0006 (.0003)*	.01 (.003)***	.004 (.003)
Rain Shock at Age 3	-.01 (.006)**	-.002 (.007)	-.003 (.007)	-.0002 (.0003)	.005 (.002)*	.01 (.003)***
Rain Shock at Age 4	-.02 (.005)***	-.01 (.006)*	-.02 (.005)***	-.0004 (.0003)	-.001 (.002)	-.0006 (.003)
Observations	1,154,292	383,271	1,162,482	1,189,704	914,129	254,770
Mean Dependent Variable	2.06	.785	2.08	.009	.877	.843
Panel C: Ages 11-16						
Rain Shock Current Year	-.01 (.01)	-.04 (.02)**	.005 (.009)	-.0004 (.001)	-.001 (.003)	-.014 (.006)**
Rain Shock Previous Year	-.02 (.01)*	-.05 (.02)***	-.03 (.01)**	.004 (.002)**	-.02 (.004)***	
Rain Shock In Utero	-.005 (.004)	.003 (.003)	-.003 (.004)	.001 (.0009)	-.009 (.002)***	.01 (.002)***
Rain Shock Year of Birth	.002 (.005)	.004 (.004)	.001 (.005)	-.002 (.001)**	.007 (.002)***	.01 (.003)***
Rain Shock at Age 1	.005 (.006)	.004 (.005)	.0003 (.006)	-.002 (.001)	.01 (.003)***	.01 (.002)***
Rain Shock at Age 2	.002 (.006)	.008 (.004)*	-.0009 (.006)	.001 (.001)	.004 (.002)	.007 (.002)***
Rain Shock at Age 3	-.006 (.006)	.004 (.005)	-.006 (.005)	.003 (.001)***	-.005 (.002)**	.001 (.002)
Rain Shock at Age 4	.002 (.005)	.002 (.004)	.002 (.005)	.0005 (.001)	.004 (.002)*	.008 (.003)***
Observations	949,818	460,556	953,065	1,003,336	1,005,810	212,836
Mean Dependent Variable	3.31	1.65	3.46	.070	.688	.887

Source: Test Score Data from ASER 2005-2008. Rainfall Data from University of Delaware.

Notes: This table shows estimates β_1 , β_2 the effect of rainfall shocks on current test scores and schooling outcomes, and ζ from equation (5), the effect of early life rainfall shocks on human capital ($\frac{\partial s_2^*}{\partial w_2}$ and $\frac{d}{dw_2}(e_3^*)$, and $\frac{\partial s_2^*}{\partial w_1}$ and $\frac{d}{dw_1}(e_3^*)$, respectively). “Math Score” and “Read Score” range from 0-4. “Math Word Problem” ranges from 0-2 and was only available in 2006 and 2007. “On Track” is equal to one if age minus grade is at least six, and zero otherwise. Columns 1-5 contain fixed effects for district, year and age. Since attendance is only observed in 2008, column 6 contains fixed effects for state and age. Panel A includes the entire ASER sample ages 5-16 years, Panel B restricts to ages 5-10; and Panel C to ages 11-16. Standard errors, clustered at the district level, are reported in parentheses. ***; indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A5: Effect of Rain Shocks on Schooling and Child Labor

	<i>Dependent Variable:</i>	
	<i>Attends School</i>	<i>Works</i>
Panel A: Ages 5-16		
Rain Shock Current Year	-.01 (.003) ^{***}	.005 (.001) ^{***}
Rain Shock Previous Year	-.004 (.003)	.001 (.001)
Rain Shock in Utero	-.003 (.003)	-.001 (.002)
Rain Shock in Year of Birth	.01 (.003) ^{***}	-.003 (.002) [*]
Rain Shock at Age 1	.009 (.003) ^{***}	-.005 (.001) ^{***}
Rain Shock at Age 2	.006 (.003) ^{**}	-.003 (.001) ^{**}
Rain Shock at Age 3	.003 (.003)	-.003 (.001) ^{**}
Rain Shock at Age 4	.009 (.003) ^{***}	-.005 (.001) ^{***}
Observations	297,470	299,271
Mean Dependent Variable	.795	.053
Panel B: Ages 5-10		
Rain Shock Current Year	-.005 (.004)	.002 (.0006) ^{***}
Rain Shock Previous Year	-.002 (.004)	.001 (.0008)
Rain Shock in Utero	-.003 (.003)	-.002 (.0006) ^{***}
Rain Shock in Year of Birth	-.002 (.003)	-.001 (.0004) ^{***}
Rain Shock at Age 1	-.007 (.003) ^{***}	-.0008 (.0007)
Rain Shock at Age 2	.006 (.003) [*]	-.001 (.0006) ^{**}
Rain Shock at Age 3	-.005 (.003) [*]	-.0006 (.0007)
Rain Shock at Age 4	-.008 (.003) ^{***}	.0006 (.0005)
Observations	154,291	155,274
Mean Dependent Variable	.821	.007
Panel C: Ages 11-16		
Rain Shock Current Year	-.02 (.003) ^{***}	.008 (.002) ^{***}
Rain Shock Previous Year	-.008 (.003) ^{**}	.002 (.002)
Rain Shock in Utero	.003 (.002)	-.003 (.002) [*]
Rain Shock in Year of Birth	.01 (.002) ^{***}	-.004 (.002) ^{**}
Rain Shock at Age 1	.009 (.002) ^{***}	-.007 (.002) ^{***}
Rain Shock at Age 2	.001 (.002)	-.003 (.002)
Rain Shock at Age 3	.0005 (.003)	-.004 (.002) [*]
Rain Shock at Age 4	.008 (.003) ^{***}	-.006 (.002) ^{***}
Observations	143,179	143,997
Mean Dependent Variable	.766	.103

Source: Measures of attends school and child labor from rounds 60, 61, 62, and 64 of NSS. Rainfall data from University of Delaware.

Notes: This table shows estimates of β_1 , β_2 , and ζ from equation (5), the effect of contemporaneous and early life rain shocks on school attendance and working ($\frac{\partial s_2^*}{\partial w_2}$ and $\frac{\partial s_2^*}{\partial w_1}$). Panel A restricts the sample to children ages 5-16 years old, Panel B to ages 5-10; and Panel C to ages 11-16. All regressions contain district fixed effects and control for age and sex. All columns contain controls for early life rainfall shock exposure (in utero-age 4). Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A6: Effect of Contemporaneous Rainfall Shocks on Human Capital (Boys)

	<i>Dependent Variable:</i>				
	Math Score	Math Word Problem	Read Score	Dropped Out	Attendance
Rain Shock Current Year	-0.01 (.01)	-0.05 (.02)***	.003 (.01)	-.0004 (.0008)	-.02 (.006)***
Rain Shock Previous Year	-0.01 (.01)	-.04 (.02)**	-.02 (.01)*	.002 (.0009)**	-.03 (.008)***
Observations	1145,955	465,547	1152,131	1192,358	250,178
Mean Dependent Variable	2.66	1.281	2.723	0.035	0.863

Source: Test Score Data from ASER 2005-2008. Rainfall Data from University of Delaware.

Notes: This table shows estimates of β_1 and β_2 from equation (5), the effect of rainfall shocks on current test scores for boys ages 5-16 ($\frac{\partial s_2^*}{\partial w_2}$ and $\frac{d}{dw_2}(e_3^*)$). Columns 1-4 contain fixed effects for district, year and age. Since attendance is only observed in 2008, column 5 contains fixed effects for state, year, and age. All columns contain controls for early life rainfall shock exposure (in utero-age 4). Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A7: Effect of Contemporaneous Rainfall Shocks on Human Capital (Girls)

	<i>Dependent Variable:</i>				
	Math Score	Math Word Problem	Read Score	Dropped Out	Attendance
Rain Shock Current Year	-.02 (.01)*	-.05 (.02)***	.002 (.01)	.0008 (.0008)	-.02 (.006)***
Rain Shock Previous Year	-.02 (.01)*	-.04 (.02)*	-.02 (.01)*	.002 (.0009)**	-.04 (.009)***
Observations	951,233	378,280	956,529	988,483	208,602
Mean Dependent Variables	2.567	1.225	2.662	0.039	0.863

Source: Test Score Data from ASER 2005-2008. Rainfall Data from University of Delaware.

Notes: This table shows estimates of β_1 and β_2 from equation (5), the effect of rainfall shocks on current test scores for girls ages 5-16 ($\frac{\partial s_2^*}{\partial w_2}$ and $\frac{d}{dw_2}(e_3^*)$). Columns 1-4 contain fixed effects for district, year and age. Since attendance is only observed in 2008, column 5 contains fixed effects for state, year, and age. All columns contain controls for early life rainfall shock exposure (in utero-age 4). Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A8: Effect of Early Life Rainfall Shocks on Human Capital (Boys)

	<i>Dependent Variable:</i>				
	Math Score	Math Word Problem	Read Score	Never Enrolled	On Track
Rain Shock In Utero	.008 (.004)*	.003 (.006)	.01 (.005)**	-.001 (.0004)***	.02 (.002)***
Rain Shock Year of Birth	.01 (.004)**	.01 (.006)*	.008 (.004)*	-.002 (.0004)***	.02 (.002)***
Rain Shock at Age 1	.01 (.005)**	.02 (.006)***	.01 (.005)**	-.002 (.0005)***	.01 (.002)***
Rain Shock at Age 2	.01 (.004)***	.02 (.006)***	.01 (.004)***	-.003 (.0004)***	.01 (.002)***
Rain Shock at Age 3	.006 (.005)	.01 (.006)**	.01 (.005)**	-.002 (.0004)***	-.0002 (.002)
Rain Shock at Age 4	.003 (.005)	-.008 (.006)	.01 (.005)**	-.002 (.0004)***	.002 (.002)
Observations	1,271,233	465,547	1,277,571	1,297,538	959,304
Mean Dependent Variable	2.66	1.281	2.723	0.026	0.811

Source: Test Score Data from ASER 2005-2009. Rainfall Data from University of Delaware.

Notes: This table shows estimates of ζ from equation (6), the effect of early life rainfall shocks on current test scores and schooling outcomes restricted to boys only ($\frac{\partial s_2^*}{\partial w_1}$ and $\frac{d}{dw_1}(e_3^*)$). “Math Score” and “Read Score” range from 0-4. “Math Word Problem” ranges from 0-2, and was only asked in 2006 and 2007. “On Track” is equal to one if age minus grade is at least six, and zero otherwise. All regressions contain fixed effects for household, year and age. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A9: Effect of Early Life Rainfall Shocks on Human Capital (Girls)

	<i>Dependent Variable:</i>				
	maths score	Math Word Problem	Read Score	Never Enrolled	On Track
Rain Shock in Utero	.02 (.005)***	.009 (.006)	.02 (.005)***	-.002 (.0006)***	.03 (.003)***
Rain Shock Year of Birth	.01 (.005)**	.005 (.007)	.01 (.006)**	-.002 (.0006)***	.02 (.003)***
Rain Shock at Age 1	.01 (.005)***	.01 (.007)	.02 (.005)***	-.003 (.0005)***	.02 (.003)***
Rain Shock at Age 2	.007 (.005)	.01 (.007)**	.01 (.005)**	-.003 (.0006)***	.01 (.003)***
Rain Shock at Age 3	-.005 (.005)	-.002 (.007)	.002 (.005)	-.001 (.0006)*	-.0002 (.002)
Rain Shock at Age 4	-.003 (.005)	-.01 (.007)*	.009 (.005)*	-.002 (.0005)***	.0000306 (.002)
Observations	1,057,467	378,280	1,062,888	1,079,939	808,469
Mean Dependent Variable	2.567	1.225	2.662	0.035	0.811

Source: Test Score Data from ASER 2005-2009. Rainfall Data from University of Delaware.

Notes: This table shows estimates of ζ from equation (6), the effect of early life rainfall shocks on current test scores and schooling outcomes restricted to girls only ($\frac{\partial s_2^*}{\partial w_1}$ and $\frac{d}{dw_1}(e_3^*)$). “Math Score” and “Read Score” range from 0-4. “Math Word Problem” ranges from 0-2, and was only asked in 2006 and 2007. “On Track” is equal to one if age minus grade is at least six, and zero otherwise. All regressions contain fixed effects for household, year and age. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A10: Effect of Rain Shocks on Days Sick and Health Expenditures

	Days sick	Health expenditures (ln Rs)
Rain Shock Current Year	-.52 (.22)**	-.22 (.07)***
Rain Shock Previous Year	-.38 (.22)*	.005 (.1)
Observations	6293	6293
Mean Dependent Variable	6.07	4.28

Source: IHDS 2004–2005 data for children ages 5-16. Rainfall data from the University of Delaware.

Notes: This table shows estimates of the effect of rainfall shocks on number of days sick in last month due to diarrhea, fever, and/or cough and health expenditures (hospital, doctor, medicine, tests, and transport) for children ages 5-16. Each cell is a separate OLS regression. All regressions contain age, gender and state 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 A11: Effect of Rain Shocks on Test Scores in High Malaria States

	<i>Dependent Variable:</i>	
	Math Score	Reading Score
Rain Shock Current Year	-.08 (.03)**	-.03 (.03)
Malaria state	-.14 (.12)	-.1 (.12)
Rain shock*Malaria state	.07 (.07)	.03 (.06)
Rain Shock Previous Year	.04 (.03)	.02 (.03)
Observations	1,892,741	2,115,547

Source: Test Score Data from ASER 2005-2009. Rainfall Data from University of Delaware.

Notes: This table shows estimates β_1 , the effect of rainfall shocks on current test scores and schooling outcomes interacted with a dummy for the five high malaria states (Orissa, Chhattisgarh, West Bengal, Jharkhand, and Karnataka). All specifications include state-region fixed effects and are clustered at the state level. All columns contain controls for early life rainfall shock exposure (in utero-age 4). Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A12: Are Teacher Absences or School Lunches Driving the Results?

<i>Dependent Variable:</i>	Teacher Absence Rate	Midday Meal Provision
Rain Shock Current Year	-.03 (.01)**	.04 (.02)**
Rain Shock Previous Year	.002 (.01)	.06 (.02)***
Observations	20,297	24,203
Mean Dependent Variable	0.18	0.81

Source: Teacher absence rates and midday meal provision data from the 2005 and 2007 ASER School Survey.

Notes: This table shows the coefficients of rainfall shocks on teacher absence rates and midday meal provision in a linear regression. All regressions contain village and year 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 A13: Does Drought Impact Fertility Decisions?

	In cohort size (born 1991) (1)	In cohort size (born 2001) (2)	In cohort size (born 2001) (3)
Drought (t)	-.01 (.02)	-.01 (.02)	-.01 (.02)
Drought In utero (t-1)	.04 (.06)	-.002 (.03)	-.005 (.03)
Drought (t-2)	.008 (.02)	-.04 (.02)	-.04 (.02)
Drought (t-3)	-.04 (.04)	.03 (.06)	.03 (.06)
Drought (t-4)	-.02 (.02)	.09 (.03)***	.09 (.03)***
Drought (t-5)	-.03 (.03)	-.02 (.03)	-.02 (.03)
In Population 1991	.04 (.02)**		
In Population 2001		.02 (.02)	
In Female Population 2001 (15-49)			.01 (.02)
Observations	104,631	207,905	205,728
Mean Dependent Variable	5.33	5.98	5.98

Source: Number of births in each district in 1991 and 2001 using Indian Census Data. Rainfall data from the University of Delaware.

Notes: These are OLS regressions where the dependent variable is ln number of births in each district in 1991 and 2001. All regressions contain state and year of survey fixed effects. Standard errors are clustered at the district level and are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A14: Effect of Rain Shocks on Migration Rates

	Has Not Moved (Last Six Months)			
	Full Sample	Ages 5-16	Full Sample	Ages 5-16
Drought This Year	.001 (.003)	.002 (.003)		
Drought Last Year	.006 (.003)*	.006 (.004)		
Positive Shock This Year			-.003 (.01)	.007 (.009)
Positive Shock Last Year			.0002 (.007)	-.001 (.007)
Observations	236,429	67,521	236,429	67,521
Mean Dependent Variable	.987	.987	.987	.987

Source: Migration data from NSS round 55 (1999-2000). Rainfall data from the University of Delaware.

Notes: These are OLS regressions where the dependent variable is has not moved from district in past six months or more, and the independent variable is rain shocks. In odd numbered columns we use the entire sample and in all even numbered columns we restrict the sample to children ages 5-16. All regressions contain state fixed effects. Standard errors are clustered at the district level and are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Mathematical Appendix

Parents maximize total household utility:

$$\max_{c_2, s_2} \{u_1(c_1) + \beta u_2(c_2) + \beta^2 V(e_3)\}$$

subject to the constraints that

$$c_2 \leq w_2(h + (1 - s_2)e_2)$$

$$c_1 \leq w_1 h$$

$$s_2 \in [0, 1]$$

$$e_3 = f_3(e_2, c_2, s_2) = f_3(e_2, w_2(h + (1 - s_2)e_2), s_2)$$

and we have assumed that

$$V(e_3) = e_3$$

Since no decisions are made in the first period, we can rewrite the maximization problem as

$$\max_{s_2 \in [0, 1], c_2} \{u_2(c_2) + \beta f_3(e_2, c_2, s_2)\} \text{ s.t. } c_2 \leq w_2(h + (1 - s_2)e_2)$$

The Lagrangian for this problem is:

$$\mathcal{L} = u_2(c_2) + \beta f_3(e_2, s_2, c_2) + \lambda [w_2(h + (1 - s_2)e_2) - c_2]$$

Given the assumptions laid out in Section 2, the first order conditions will be necessary and sufficient to characterize a unique optimum:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \lambda} &= w_2 (h + (1 - s_2^*(w_2, e_2) e_2)) - c_2^*(w_2, e_2) = & 0 \\
\frac{\partial \mathcal{L}}{\partial c_2} &= u'(c_2^*(w_2, e_2)) + \beta \frac{\partial f_3}{\partial c_2}(e_2, c_2^*(w_2, e_2), s_2^*(w_2, e_2)) - \lambda^*(w_2, e_2) = & 0 \\
\frac{\partial \mathcal{L}}{\partial s_2} &= \beta \frac{\partial f_3}{\partial s_2}(e_2, c_2^*(w_2, e_2), s_2^*(w_2, e_2)) - \lambda^*(w_2, e_2) \cdot w_2 e_2 = & 0
\end{aligned}$$

Rearranging yields the single first-order condition outlined in the text of Section 2:

$$w_2 e_2 \frac{\partial u_2}{\partial c_2} = \beta \left(\frac{\partial f_3}{\partial s_2} - w_2 e_2 \frac{\partial f_3}{\partial c_2} \right)$$

We define the function

$$\Theta(w_2, e_2, c_2^*, s_2^*) = \left(\frac{\partial f_3}{\partial s_2} - w_2 e_2 \frac{\partial f_3}{\partial c_2} \right)$$

so we can rewrite the first order condition as

$$w_2 e_2 \frac{\partial u_2}{\partial c_2} = \beta \Theta$$

Effect of School-Aged Wages on Schooling and Human Capital

Beginning from the first order condition,

$$\text{F.O.C.: } w_2 e_2 \frac{\partial u_2}{\partial c_2} = \beta \left(\frac{\partial f_3}{\partial s_2} - w_2 e_2 \frac{\partial f_3}{\partial c_2} \right)$$

We can take the total derivative with respect to w_2 (noting that $e_2 = f_2(w_1 h)$ and $e_3 = f_3(w_1 h, w_2(h + (1 - s_2)e_2), s_2)$):

$$\left[\frac{\partial^2 u_2}{\partial c_2^2} w_2 e_2 \left((h + (1 - s_2^*) e_2) - w_2 e_2 \frac{\partial s_2^*}{\partial w_2} \right) + e_2 \frac{\partial u_2}{\partial c_2} \right] =$$

$$\beta \left[\frac{\partial^2 f_3}{\partial s_2 \partial c_2} \left((h + (1 - s_2^*) e_2) - w_2 e_2 \frac{\partial s_2^*}{\partial w_2} \right) + \frac{\partial^2 f_3}{\partial s_2^2} \frac{\partial s_2^*}{\partial w_2} \right]$$

$$-\beta \left[\left(\frac{\partial^2 f_3}{\partial c_2^2} \left((h + (1 - s_2^*) e_2) - w_2 e_2 \frac{\partial s_2^*}{\partial w_2} \right) + \frac{\partial^2 f_3}{\partial c_2 \partial s_2} \frac{\partial s_2^*}{\partial w_2} \right) e_2 w_2 + e_2 \frac{\partial f_3}{\partial c_2} \right]$$

and solve for $\frac{\partial s_2^*}{\partial w_2}$

$$\frac{\partial s_2^*}{\partial w_2} = \frac{\frac{\partial^2 u_2}{\partial c_2^2} w_2 e_2 (h + (1 - s_2^*) e_2) + e_2 \frac{\partial u_2}{\partial c_2} - \beta \left[\frac{\partial^2 f_3}{\partial s_2 \partial c_2} (h + (1 - s_2^*) e_2) - \frac{\partial^2 f_3}{\partial c_2^2} (h + (1 - s_2^*) e_2) e_2 w_2 - e_2 \frac{\partial f_3}{\partial c_2} \right]}{w_2^2 e_2^2 \frac{\partial^2 u_2}{\partial c_2^2} + \beta \left[\frac{\partial^2 f_3}{\partial s_2^2} + w_2^2 e_2^2 \frac{\partial^2 f_3}{\partial c_2^2} - 2e_2 w_2 \frac{\partial^2 f_3}{\partial c_2 \partial s_2} \right]}$$

Since, by assumption

$$w_2^2 e_2^2 \frac{\partial^2 u_2}{\partial c_2^2} + \beta \left[\frac{\partial^2 f_3}{\partial s_2^2} + w_2^2 e_2^2 \frac{\partial^2 f_3}{\partial c_2^2} - 2e_2 w_2 \frac{\partial^2 f_3}{\partial c_2 \partial s_2} \right] < 0$$

we can write that

$$\frac{\partial s_2^*}{\partial w_2} \propto -\frac{\partial^2 u_2}{\partial c_2^2} w_2 e_2 (h + (1 - s_2^*) e_2) - e_2 \frac{\partial u_2}{\partial c_2}$$

$$+\beta \left[\frac{\partial^2 f_3}{\partial s_2 \partial c_2} (h + (1 - s_2^*) e_2) - \frac{\partial^2 f_3}{\partial c_2^2} (h + (1 - s_2^*) e_2) e_2 w_2 - e_2 \frac{\partial f_3}{\partial c_2} \right]$$

Rearranging slightly,

$$\frac{\partial s_2^*}{\partial w_2} \propto -e_2 \left(\frac{\partial u_2}{\partial c_2} + \beta \frac{\partial f_3}{\partial c_2} \right) - (h + (1 - s_2^*) e_2) w_2 e_2 \frac{\partial^2 u_2}{\partial c_2^2} + (h + (1 - s_2^*) e_2) \beta \left[\frac{\partial^2 f_3}{\partial s_2 \partial c_2} - \frac{\partial^2 f_3}{\partial c_2^2} e_2 w_2 \right]$$

And since

$$\Theta = \frac{\partial f_3}{\partial s_2} - w_2 e_2 \frac{\partial f_3}{\partial c_2}$$

$$\frac{\partial \Theta}{\partial c_2} = \frac{\partial^2 f_3}{\partial s_2 \partial c_2} - e_2 w_2 \frac{\partial^2 f_3}{\partial c_2^2}$$

And substituting this into the above equation yields

$$\frac{\partial s_2^*}{\partial w_2} \propto -e_2 \left(\frac{\partial u_2}{\partial c_2} + \beta \frac{\partial f_3}{\partial c_2} \right) - (h + (1 - s_2^*) e_2) w_2 e_2 \frac{\partial^2 u_2}{\partial c_2^2} + (h + (1 - s_2^*) e_2) \beta \frac{\partial \Theta}{\partial c_2}$$

In addition, since we know that

$$e_3^* = f_3(e_2, c_2^*, s_2^*)$$

we can write the effect of school-aged wages on later-life human capital:

$$\begin{aligned} \frac{d}{dw_2} (f_3(e_2, c_2^*, s_2^*)) &= \frac{\partial f_3}{\partial c_2} \frac{\partial c_2^*}{\partial w_2} + \frac{\partial f_3}{\partial s_2} \frac{\partial s_2^*}{\partial w_2} \\ &= \frac{\partial f_3}{\partial c_2} \left(h + (1 - s_2^*) e_2 - w_2 e_2 \frac{\partial s_2^*}{\partial w_2} \right) + \frac{\partial f_3}{\partial s_2} \frac{\partial s_2^*}{\partial w_2} \\ &= (h + (1 - s_2) e_2) \frac{\partial f_3}{\partial c_2} + \Theta \frac{\partial s_2^*}{\partial w_2} \end{aligned}$$

Effect of Early Life Wages on Schooling and Human Capital

Beginning from the first order condition,

$$\text{F.O.C.: } \frac{\partial u_2}{\partial c_2} w_2 e_2 = \beta \left(\frac{\partial f_3}{\partial s_2} - w_2 e_2 \frac{\partial f_3}{\partial c_2} \right)$$

Noting as in the text, that

$$\frac{d}{dw_1} (e_2) = \frac{\partial f_2}{\partial c_1} \frac{\partial c_1}{\partial w_1} = h \frac{\partial f_2}{\partial c_1} > 0$$

and in order to understand the effect of early life wages on schooling and later-life human

capital, it is sufficient to study the effect of period 2 human capital on these variables:

$$\frac{\partial s_2^*}{\partial w_1} = h \frac{\partial f_2}{\partial c_1} \frac{\partial s_2^*}{\partial e_2} \propto \frac{\partial s_2^*}{\partial e_2}$$

We can take the total derivative of the first order condition with respect to e_2 (noting that $e_2 = f_2(w_1 h)$ and $e_3 = f_3(w_1 h, w_2(h + (1 - s_2)e_2), s_2)$):

$$\begin{aligned} & w_2 e_2 \left(w_2 (1 - s_2^*) - w_2 e_2 \frac{\partial s_2^*}{\partial e_2} \right) \frac{\partial^2 u_2}{\partial c_2^2} + w_2 \frac{\partial u_2}{\partial c_2} = \\ & \beta \left[\frac{\partial^2 f_3}{\partial s_2 \partial e_2} + \frac{\partial^2 f_3}{\partial s_2 \partial c_2} \left(w_2 (1 - s_2^*) - w_2 e_2 \frac{\partial s_2^*}{\partial e_2} \right) + \frac{\partial^2 f_3}{\partial s_2^2} \frac{\partial s_2^*}{\partial e_2} \right] \\ & - \beta \left[w_2 e_2 \left(\frac{\partial^2 f_3}{\partial c_2 \partial e_2} + \frac{\partial^2 f_3}{\partial c_2^2} \left(w_2 (1 - s_2^*) - w_2 e_2 \frac{\partial s_2^*}{\partial e_2} \right) + \frac{\partial^2 f_3}{\partial c_2 \partial s_2} \frac{\partial s_2^*}{\partial e_2} \right) + w_2 \frac{\partial f_3}{\partial c_2} \right] \end{aligned}$$

Rearranging, we have

$$\frac{\partial s_2^*}{\partial e_2} = \frac{-w_2^2 e_2 (1 - s_2^*) \frac{\partial^2 u_2}{\partial c_2^2} - w_2 \frac{\partial u_2}{\partial c_2} + \beta \left[\frac{\partial^2 f_3}{\partial s_2 \partial e_2} + w_2 (1 - s_2^*) \left(\frac{\partial^2 f_3}{\partial s_2 \partial c_2} - w_2 e_2 \frac{\partial^2 f_3}{\partial c_2^2} \right) - w_2 e_2 \frac{\partial^2 f_3}{\partial c_2 \partial e_2} - w_2 \frac{\partial f_3}{\partial c_2} \right]}{-w_2^2 e_2^2 \frac{\partial^2 u_2}{\partial c_2^2} - \beta \left[\frac{\partial^2 f_3}{\partial s_2^2} - 2w_2 e_2 \frac{\partial^2 f_3}{\partial s_2 \partial c_2} + w_2^2 e_2^2 \frac{\partial^2 f_3}{\partial c_2^2} \right]}$$

and since, by assumption,

$$-w_2^2 e_2^2 \frac{\partial^2 u_2}{\partial c_2^2} - \beta \left[\frac{\partial^2 f_3}{\partial s_2^2} - 2w_2 e_2 \frac{\partial^2 f_3}{\partial s_2 \partial c_2} + w_2^2 e_2^2 \frac{\partial^2 f_3}{\partial c_2^2} \right] > 0$$

$$\begin{aligned} & \frac{\partial s_2^*}{\partial e_2} \propto -w_2^2 e_2 (1 - s_2^*) \frac{\partial^2 u_2}{\partial c_2^2} - w_2 \frac{\partial u_2}{\partial c_2} + \\ & \beta \left[\frac{\partial^2 f_3}{\partial s_2 \partial e_2} + w_2 (1 - s_2^*) \left(\frac{\partial^2 f_3}{\partial s_2 \partial c_2} - w_2 e_2 \frac{\partial^2 f_3}{\partial c_2^2} \right) - w_2 e_2 \frac{\partial^2 f_3}{\partial c_2 \partial e_2} - w_2 \frac{\partial f_3}{\partial c_2} \right] \end{aligned}$$

and since

$$\Theta = \frac{\partial f_3}{\partial s_2} - w_2 e_2 \frac{\partial f_3}{\partial c_2}$$

we can rewrite this expression as

$$\frac{\partial s_2^*}{\partial e_2} \propto -w_2^2 e_2 (1 - s_2^*) \frac{\partial^2 u_2}{\partial c_2^2} - w_2 \frac{\partial u_2}{\partial c_2} + \beta \left[\frac{\partial \Theta}{\partial e_2} + w_2 (1 - s_2^*) \frac{\partial \Theta}{\partial c_2} \right]$$

In addition, since we know that

$$e_3^* = f_3(e_2, c_2^*, s_2^*)$$

we can write the effect of school-aged human capital on later-life human capital:

$$\begin{aligned} \frac{d}{de_2} (e_3^*) &= \frac{\partial f_3}{\partial e_2} + \frac{\partial f_3}{\partial c_2} \frac{\partial c_2^*}{\partial e_2} + \frac{\partial f_3}{\partial s_2} \frac{\partial s_2^*}{\partial e_2} \\ &= \frac{\partial f_3}{\partial e_2} + \frac{\partial f_3}{\partial c_2} \left(w_2 (1 - s_2^*) - w_2 e_2 \frac{\partial s_2^*}{\partial e_2} \right) + \frac{\partial f_3}{\partial s_2} \frac{\partial s_2^*}{\partial e_2} \\ &= \frac{\partial f_3}{\partial e_2} + \frac{\partial f_3}{\partial c_2} w_2 (1 - s_2^*) + \Theta \frac{\partial s_2^*}{\partial e_2} \end{aligned}$$

Discussion Section 4.4

From Equation 1,

$$\frac{\partial s_2^*}{\partial w_2} \propto -e_2 \left(\frac{\partial u_2}{\partial c_2} + \beta \frac{\partial f_3}{\partial c_2} \right) - (h + (1 - s_2^*) e_2) w_2 e_2 \frac{\partial^2 u_2}{\partial c_2^2} + (h + (1 - s_2^*) e_2) \beta \frac{\partial \Theta}{\partial c_2}$$

Combined with our empirical finding that $\frac{\partial s_2^*}{\partial w_2} < 0$ implies that

$$-(h + (1 - s_2^*) e_2) w_2 e_2 \frac{\partial^2 u_2}{\partial c_2^2} + (h + (1 - s_2^*) e_2) \beta \frac{\partial \Theta}{\partial c_2} < e_2 \left(\frac{\partial u_2}{\partial c_2} + \beta \frac{\partial f_3}{\partial c_2} \right)$$

Rearranging,

$$w_2^2 e_2 (1 - s_2^*) \frac{\partial^2 u_2}{\partial c_2^2} - \beta w_2 (1 - s_2^*) \frac{\partial \Theta}{\partial c_2} > - \frac{w_2 (1 - s_2^*) e_2 \left(\frac{\partial u_2}{\partial c_2} + \beta \frac{\partial f_3}{\partial c_2} \right)}{(h + (1 - s_2^*) e_2)} \quad (\text{A1})$$

In addition, from Equation 3,

$$\frac{\partial s_2^*}{\partial w_1} \propto \frac{\partial s_2^*}{\partial e_2} \propto -w_2^2 e_2 (1 - s_2^*) \frac{\partial^2 u_2}{\partial c_2^2} - w_2 \frac{\partial u_2}{\partial c_2} + \beta \left[\frac{\partial \Theta}{\partial e_2} + w_2 (1 - s_2^*) \frac{\partial \Theta}{\partial c_2} \right]$$

Combining this with our empirical finding that $\frac{\partial s_2^*}{\partial w_1} > 0$

$$\beta \frac{\partial \Theta}{\partial e_2} > w_2 \frac{\partial u_2}{\partial c_2} + w_2^2 e_2 (1 - s_2^*) \frac{\partial^2 u_2}{\partial c_2^2} - \beta w_2 (1 - s_2^*) \frac{\partial \Theta}{\partial c_2}$$

Substituting for the final two terms with Equation (A1),

$$\beta \frac{\partial \Theta}{\partial e_2} > w_2 \frac{\partial u_2}{\partial c_2} - \frac{w_2 (1 - s_2^*) e_2 \left(\frac{\partial u_2}{\partial c_2} + \beta \frac{\partial f_3}{\partial c_2} \right)}{(h + (1 - s_2^*) e_2)}$$

And rearranging,

$$\beta \frac{\partial \Theta}{\partial e_2} > w_2 \left[\frac{h}{(h + (1 - s_2^*) e_2)} \frac{\partial u_2}{\partial c_2} - \frac{(1 - s_2^*) e_2}{(h + (1 - s_2^*) e_2)} \beta \frac{\partial f_3}{\partial c_2} \right]$$