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

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Abstract

Higher wages are generally thought to increase human capital production, particularly in the developing world. We introduce a simple model of human capital production which predicts that wages can negatively impact human capital under reasonable assumptions. Using data on test scores and schooling from rural India, we show that human capital investment is procyclical in early life (in utero to age 3) but then becomes countercyclical. We argue that, consistent with our model, this countercyclical effect is caused by families investing more time in schooling when outside options are worse. In addition, we find long term impacts of these shocks: adults who experienced more positive rainfall shocks during school years have lower overall total years of schooling. These results suggest that the opportunity cost of schooling, even for fairly young children, is an important factor in determining overall human capital investment.

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1 Introduction

Human capital investment is an important determinant of economic growth (Mankiw et al., 1992). However, there is still much debate over the determinants of human capital investment. The majority of empirical evidence from poor countries suggests the relationship is procyclical (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 countercyclical human capital investment (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 children react to higher wages by leaving school early to join the workforce, it could raise overall inequality in poor countries or even stunt long term growth.

We argue that at least part of the differences in these studies may be due to differential effects by age. In particular, if the opportunity cost of time for older children is affected by wages, then we would expect that the substitution effect would be more powerful 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 at earlier ages), then we might also expect to see differential impacts of wage shocks by age. In this paper, we introduce a simple model of human capital investment from which we derive predictions about the effects of wages on human capital. Under certain conditions, our model predicts that wages during school years will negatively affect both schooling investment and overall human capital. In addition, the model predicts that in the presence of strong complementarity between early life consuption and later-life schooling investments, early life wages will positively affect both schooling investment and overall human capital.

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

We then take these predictions to the data, 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 state in India. The data includes four distinct measures of literacy and numeracy for each child whether 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 was 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.

We find that, as our theory predicts, during years with positive rainfall shocks, school-age children score lower on simple math tests. In addition, when rainfall is higher, children are less likely to attend school and are more likely to be working. In addition, children who experienced a positive rainfall shock in the previous year are more likely to have dropped out of school and less likely to be in the correct grade for their age.

We also estimate the impacts of early life rainfall shocks 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. In addition, children who experience positive rainfall shocks before age 5 are more likely to be enrolled in school and less likely to be off track in school. Lastly, we investigate whether there are long-term impacts of these rainfall shocks on total years of schooling for adults aged 16-30 using the 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 particulary detrimental to human capital investment during this period.

Our contribution to this literature is threefold. First, as far as we know, this is the

[2]This 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.

first paper to document the possibility that positive productivity shocks can lead to lower levels of human capital attainment directly using test scores. Test scores are a much better measure of human capital as they measure output/production as opposed to the previous literature which has focused on school enrollment. Second, unlike the previous literature which focuses on shocks at certain critical ages in a child's development, we focus on 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 ages of a child's human capital development. We show that human capital investment is procyclical from the in utero phase to age three, but then becomes counter cyclical. Lastly, 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 years). This constitutes a substantial shock to human capital attainment during a period when most children will already be on the margin between dropping out and continuing.

The findings from this paper are important from a policy perspective since wage subsidy programs such as NREGA in India have become a popular means of redistribution as they provide aid to the poor along with corresponding work incentives.[3] However, wage subsidies affect not only overall income, but also the prevailing wage and time cost of family members. For example, NREGA, a massive program which generated 2.57 billion person-days of employment (in 2010-2011) boosted the real daily agricultural wage rate 5.3 per cent (Berg et al., 2012). It is possible such wage subsidy programs could lead to decreased human capital production for certain individuals.

[3]Recent examples include programs in Malawi, Bangladesh, India, Philippines, Zambia, Ethiopia, Sri Lanka, Chile, Uganda, and Tanzania. However, the practice of imposing work requirements for welfare programs stretches back at least to the British Poor Law of 1834 (Imbert and Papp, 2012).

2 A Simple Model of Human Capital Investment

We consider a simple model of human capital investment in which households get utility from consumption and human capital. Households consist of one child and one parent, and the parent maximizes the lifetime utility of the child.[4] 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 (s_t) or working ($1 - s_t$). In the third period, the child gets a payoff from her accumulated human capital, e_3.

Thus, the parent maximizes

$$\max_{s_2} \left\{ u\left(c_1\right) + \beta u\left(c_2\right) + \beta^2 \left(V\left(e_3\right)\right) \right\}$$

where c_t is the consumption of the child in period t, e_t is the human capital of the child in period t, $V(\cdot)$ is the value function of human capital, β is the discount rate, and $u(c)$ is the utility function, where $\frac{du}{dc} > 0$ and $\frac{d^2u}{dc^2} < 0$.

Household consumption is determined by the labor income of the parent and child. The parent inelastically supplies one unit of labor,[5] for which he is paid a wage $w_t h$ where w_t is the base wage in period t, and h is the parent's human capital. Likewise, the child earns $w_t e_t$ for the time he spends at work, $1 - s_t$. We assume that the child consumes a constant fraction of household income in each period, α. Thus, consumption of the child in each period will be

$$\begin{aligned} c_1 &= \alpha w_1 h \\ c_2 &= \alpha w_2 (h + (1 - s_2) e_2) \end{aligned}$$

[4] In the appendix we include a selfish parents extension, but in the main model we assume parents are altruistic.

[5] Note that there is no leisure in this model.

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 their children. This is sensible in the context of rural India since primary school is free and compulsory,[6] and the Indian government has built many schools to keep the costs of attendance low.[7] 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 and/or numeracy.

In our three period model, human capital in period 1 is normalized to zero,[8] and human capital in period 2 is only a function of the child'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 consumption in both periods and schooling in period 2. Thus, we have

$$
\begin{aligned}
e_1 =& 0 \\
e_2 =& f_2(c_1) = f_2(\alpha w_1 h) \\
e_3 =& f_3\left(e_2, c_2, s_2\right) = f_3(f_2(\alpha w_1 h), \alpha w_2\left(h + \left(1 - s_2\right) e_2\right), s_2)
\end{aligned}
$$

We can rewrite the parent's maximization problem as[9]

$$
\max_{s_2} \left\{ u\left(\alpha w_1 h\right) + \beta u\left(\alpha w_2\left(h + \left(1 - s_2\right) e_2\right)\right) + \beta^2\left(f_3\left(\alpha w_1 h, \alpha w_2 (h + (1 - s_2) e_2), s_2\right)\right) \right\}
$$

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

[7]For 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).

[8]Note that there is no heterogeneity of ability across children in this model. This will not qualitatively change the results.

[9]For ease of exposition,we will let $f_i(\cdot) = V(f_i(\cdot))$ for the remainder of the paper. Relaxing this assumption does not qualitatively change results. We will assume that $\frac{\partial f_3}{\partial c_2} \geq 0$, $\frac{\partial f_3}{\partial s_2} \geq 0$, 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.

Taking the first order condition with respect to the schooling decision yields

$$FOC: \quad \beta \frac{du}{dc} \alpha w_2 e_2 - \beta^2 \frac{df_3}{ds_2} = 0$$

where

$$\frac{df_3}{ds_2} = \frac{\partial f_3}{\partial s_2} + \frac{\partial f_3}{\partial c_2}\frac{\partial c_2}{\partial s_2} = \frac{\partial f_3}{\partial s_2} - \frac{\partial f_3}{\partial c_2}(\alpha w_2 e_2)$$

When deciding how much schooling the child should get, the parent trades off more consumption now and more human capital later. Assuming an interior optimum, the parent equalizes marginal utility of consumption with the marginal benefit of human capital. We are interested in the effect that wages have on the optimal level of schooling. That is, if wages increase, do families 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 total human capital.

2.1 Effect of School-Aged Wages on Human Capital

If school-aged wages increase, what happens to human capital? The comparative static shown below ($\frac{df_3}{dw_2}$) could be either positive or negative, but it can still give us insight into a few important factors.

$$\frac{df_3}{dw_2} = \overbrace{\gamma \frac{\partial f_3}{\partial c_2}}^{\text{Direct Effect of } c_2} + \overbrace{\frac{\partial f_3}{\partial s_2}\frac{\partial s_2}{\partial w_2}}^{\text{Effect of Change in } s} - \overbrace{\alpha e_2 \frac{\partial f_3}{\partial c_2}\frac{\partial s_2}{\partial w_2}}^{\text{Indirect Effect of } s \text{ on } c_2} \lesseqgtr 0$$

where

$$\frac{\partial s_2}{\partial w_2} = \Psi \left[\alpha e_2 \frac{\partial u}{\partial c} - \beta \left(\frac{\gamma}{w_2} \left(\frac{\partial^2 f_3}{\partial s_2 \partial c_2} - \alpha e_2 \frac{\partial^2 f_3}{\partial c_2^2} w_2 \right) - \alpha e_2 w_2 \frac{\partial f_3}{\partial c_2} \right) + \alpha e_2 \gamma \frac{d^2 u}{dc^2} \right] \lesseqgtr 0$$

and Ψ is the negative inverse of the second order condition and positive by assumption, and γ is a positive constant.

School-aged wages have three broad effects on human capital. First, increased wages increase the return to working which implies that higher wages in period two decrease human capital. Second, higher wages increase period 2 consumption which directly affects human capital. Lastly, higher wages could affect the returns to schooling if there are complementarities between schooling and consumption in the human capital production function. Without putting more structure on the human capital production and utility functions, we cannot say which of these effects will dominate.

We now discuss conditions under which we can derive explicit predictions about the effect of school-aged wages on human capital. First, we assume that the effect of consumption during the school years on human capital is small. That is, relative to schooling and early life consumption, consumption during later childhood does little to directly impact human capital. This is consistent with the "critical periods" literature that finds that early life consumption and investments are particularly important for later life outcomes, particularly human capital (Almond and Currie, 2011; Maccini and Yang, 2009). In addition, we assume that the utility function is not too concave so that the marginal utility of consumption does not decrease too much with additional wages. This is also a reasonable assumption given our setting of rural India.

Proposition 1.

If:

1. *The effect of school-aged consumption is relatively small* ($\frac{\partial f_3}{\partial c_2} \approx 0$)*, and*
2. *Income effects are small* ($\frac{d^2 u}{dc^2} \approx 0$)

Then:

$$\frac{\partial s}{\partial w_2} \propto -\alpha e_2 \frac{\partial u}{\partial c} < 0$$

$$\frac{df_3}{dw_2} \approx \frac{\partial f_3}{\partial s_2}\frac{\partial s_2}{\partial w_2} < 0$$

If conditions 1 and 2 hold, then the effect of school-aged wages on schooling will be negative. Since we assume that the consumption effect is small, this implies that the overall effect of wages on human capital is also negative.[10]

2.2 Effect of Early Life Wages on Human Capital

The effect of early life wages on human capital ($\frac{df_3}{dw_1}$) is also ambiguous in the general model. The mechanisms here, however, are slightly different. Early life wages affect e_3 entirely through their effect on e_2. Part of this effect is mechanical: we assume that e_2 is an input into the human capital production function. However, there are also two indirect effects. First, increased human capital during the school years increases the returns to work. Second, increased human capital in period 2 could increase the returns to schooling. That is, more investment early on in human capital might make later life investment more profitable. This is similar to the idea of "dynamic complementarities" discussed in Cunha and Heckman (2007).

$$\begin{aligned}\frac{df_3}{dw_1} = & \overbrace{\alpha h \frac{\partial f_3}{\partial c_1}}^{\text{Direct Increase in } c_1} + \overbrace{\left((\alpha w_2(1-s))\frac{\partial f_2}{\partial c_1}\alpha h\right)\frac{\partial f_3}{\partial c_2}}^{\text{Direct Increase in } c_2} \\ & - \left(\overbrace{\alpha w_2 e_2 \frac{\partial f_3}{\partial c_2}}^{\text{Indirect decrease in } c_2} - \overbrace{\frac{\partial f_3}{\partial s}}^{\text{Direct Effect of } s}\right)\frac{\partial s}{\partial w_1} \gtrless 0\end{aligned}$$

where

[10] Note that this model contains no liquidity constraints, which, in the presence of school fees or hard consumption constraints (such as starvation) could push the effect of wages on human capital in the other direction.

$$\frac{\partial s}{\partial w_1} = \Psi[\beta\left(\alpha h\left(\frac{\partial f_3^2}{\partial s_2 \partial c_1} - \alpha w_2 e_2 \frac{\partial f_3^2}{\partial c_2 \partial c_1}\right) + \delta\left(\frac{\partial f_3^2}{\partial s_2 \partial c_2} - \alpha w_2 e_2 \frac{\partial f_3^2}{\partial c_2^2}\right)\frac{\partial f_2}{\partial c_1} + \frac{\partial f_3}{\partial c_2}\frac{\partial f_2}{\partial c_1}\alpha h\right)$$

$$-\alpha w_2\left(\lambda\frac{d^2 u}{dc^2} + \frac{du}{dc}\frac{\partial f_2}{\partial c_1}\alpha h\right)] \gtreqless 0$$

and Ψ is the negative inverse of the second order condition and positive by assumption, and

$$\delta = \alpha w_2\left((1 - s_2)\alpha h\frac{\partial f_2}{\partial c_1}\right)$$

This model allows us to examine the possible forces that would affect human capital when wages increase, but without some additional structure, we cannot make explicit predictions about the effect of wages on human capital. When we apply the same two conditions used above (that the effect of school-aged consumption and income effects are both relatively small), we still cannot unambiguously sign the effect of wages on schooling. This is intuitive because even in the case in which the consumption effects in period 2 are relatively small, there is still the tradeoff of an improved outside option (due to higher human capital) versus an increased return to schooling. Since we know there will be an increased return to the outside option when early life wages are higher, if we find an increase in schooling investment ($\frac{\partial s_2}{\partial w_1} > 0$), then it must be the case that early life consumption and schooling are complements ($\frac{\partial^2 f_3}{\partial s \partial c_1} > 0$). This implies there are dynamic complementarities in the human capital production function. In addition, under these conditions, we can assert that if early life wages increase schooling investment, they will increase overall human capital.

Proposition 2.

If:

1. *The effect of school-aged consumption is relatively small ($\frac{\partial f_3}{\partial c_2} \approx 0$), and*

2. Income effects are small ($\frac{d^2u}{dc^2} \approx 0$)

Then:

$$\frac{\partial s_2}{\partial w_1} \propto \beta \frac{\partial^2 f_3}{\partial s \partial c_1} - \alpha w_2 \frac{\partial u}{\partial c}$$

and thus

$$\frac{\partial s_2}{\partial w_1} > 0 \implies \frac{\partial^2 f_3}{\partial s \partial c_1} > 0$$

Corollary 1. *If:*

1. Conditions (1) and (2) hold, and

2. $\frac{\partial s_2}{\partial w_1} > 0$

Then:

$$\frac{df_3}{dw_1} \approx \alpha h \frac{\partial f_3}{\partial c_1} + \frac{\partial f_3}{\partial s} \frac{\partial s}{\partial w_1} > 0$$

These comparative statics results suggest that increases in early life wages increase schooling and human capital. Note that the conditions in Propositions 1 and 2 are sufficient but not necessary. Thus, if we find that school-aged wage negatively impact schooling and overall human capital, this does not necessarily imply that school-aged consumption has no effect on later life human capital. It simply means that this effect is not large enough to overwhelm the effect of lower schooling. Likewise for early life wages, a positive effect of early life wages on human capital is consistent with dynamic complementarities, but it is not a direct test.

Table 8 lays out the five comparative statics from our model that we estimate: $\frac{\partial c_1}{\partial w_1}$, $\frac{\partial f_3}{\partial w_1}$, $\frac{\partial s_2}{\partial w_1}$, $\frac{\partial f_3}{\partial w_2}$, and $\frac{\partial s_2}{\partial w_2}$. As column 1 indicates, in the general form of the model, the signs of these derivatives (except for $\frac{\partial c_1}{\partial w_1}$) are ambiguous. However, under conditions 1 and 2, and in the presence of strong dynamic complementarities, we hypothesize that $\frac{\partial e_3}{\partial w_1}$, and $\frac{\partial s}{\partial w_1}$ will be positive and that $\frac{\partial e_3}{\partial w_2}$ and $\frac{\partial s}{\partial w_2}$ will be negative (see column 2 of Table 8). We test these predictions with the data in Section 4.

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.[11] We have data on children for 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 includes 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 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 Score 2). 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. Approximately 65 percent

[11] This 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`

of the children tested can recognize numbers between 1 and 9, and about 38 percent can correctly do a division problem. The reading scores are slightly higher: nearly 90 percent of children tested can recognize letters and 45 percent can read a story. In addition, the survey asks about current enrollment status and grade in school, and in 2008, attendance in the past week.[12]

3.2 Rainfall Data

To determine rainfall shock years and districts, we use monthly rainfall data which is collected by the University of Delaware.[13] The data covers all of India in the period between 1900-2008. 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 (1975-2008). 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).[14] Figure 1 shows the prevalence of drought by district over time (for the years we have cohort variation in in utero drought exposure) and indicates there is both a lot of variation over time and across districts in terms of drought exposure. Between 6 and 48 percent of districts experience a drought in any given year, and 80 percent of the districts experience at least one drought in the 16 year period that we have

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

[13] The data is available at: `http://climate.geog.udel.edu/~climate/html_pages/download.html#P2009`

[14] In 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.

child cohort variation. 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).

3.3 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 2 we will test explicitly for rainfall's effect on wages for both adults and children in rural India.

3.4 NSS Data

To examine the impact of drought on work and wages, we use the NSS (National Sample Survey) Round 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.

4 Empirical Strategy and Results

If the conditions laid out in Propositions 1 and 2 hold, then our theory makes several predictions:

1. $\frac{\partial c_1}{\partial w_1} > 0$. Early life wages unambiguously increase child consumption in early life.

2. $\frac{\partial e_3}{\partial w_2} > 0$ and $\frac{\partial s_2}{\partial w_2} > 0$. School-aged wages decrease child schooling *and* human capital

3. $\frac{\partial s_2}{\partial w_1} > 0 \implies \frac{\partial^2 f_3}{\partial s \partial c_1} > 0$. If early life wages increase school attendance, then early life consumption increases not only overall human capital, but the returns to schooling (dynamic complementarities).

4. $\frac{\partial s_2}{\partial w_1} > 0 \implies \frac{\partial e_3}{\partial w_2}$. If early life wages increase school attendance, then they also increase overall human capital.

We want to test these predictions empirically. To estimate the impact of school-aged wages on schooling and human capital, we can simply estimate the impact of current year rainfall shocks on current levels of schooling and human capital. To determine the effects of early life wages, however, we need to use lagged rainfall on current test scores, since we do not have measures of human capital for very young children. In both cases, we will be relying on the quasi-random nature of droughts and positive rainfall shocks within districts as a natural shifter of rural wages. We outline both strategies in detail below.

However, before we move to the reduced form estimation of the effect of rainfall shocks on wages, we first need to show that rainfall and agricultural productivity (and thus, wages) have a positive relationship. While 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.

In Table 2, we measure the effect of rainfall shocks on wages for children, as well as adult men and women. We find that for all three groups, positive rainfall shocks result in increased wages. Children's and women's wages are more responsive to rainfall shocks than men's wages. In Appendix 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.

4.1 Contemporaneous Rainfall Regressions

Theory predicts that if the effect of school-aged consumption is small, then we should expect to see that wages during the school years (w_2), are associated with lower levels of schooling and lower overall human capital (that is, $\frac{\partial f_3}{\partial w_2}$, and $\frac{\partial s_2}{\partial w_2}$ are negative). To test this empirically, we estimate the regression:

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

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 measures of s_2 or 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. $\beta_1 < 0$ is consistent with our model in which school-aged consumption has little impact on human capital. 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 Table 3 we report the results from Equation 1 estimating the impact of contemporaneous rainfall shocks on test scores and schooling outcomes of children aged 5-16. 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 score 2 is -.05 which means that relative to a positive rainfall year, children in a drought district score 0.1 more (or 8 percent). While rain shock this year does not impact reading scores, lagged rainfall significantly decreases these scores as well.

While rainfall shocks in the current year have little effect on age for grade or dropping out, rainfall shocks in the previous year affect both age for grade and dropping out significantly. This makes sense, given that being a drop out or being held back are variables that are likely more affected by previous behavior than behavior in the current year. Children in a positive rainfall shock year are around .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

10% from a mean of .037). Likewise, children tested in a positive shock year are about 2 percentage points less likely to be on track, relative to a drought year. In addition, children who experience a current 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.

Figure 2 shows the effects of rainfall shocks on dropout behavior does seem to increase with age. 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 4, 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 3.5 percent less likely to report attending school and 20 percent more likely to report working. Interestingly, the attendance results in Tables 3 and 4 are similar across both the datasets. 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 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. These results are consistent with both the general model and the predictions from Proposition 1.

4.2 Early Life Rainfall Exposure

We estimate the effect of early life wages on human capital for two reasons. First, our theory predicts that if schooling is increased by early life wages, then human capital will increase as well. This prediction is directly testable in the data. In addition, if we do find that early life wages increase schooling investment ($\frac{\partial s_2}{\partial w_1} > 0$), then this is evidence for dynamic complementarities in the human capital production function.

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 ($\frac{\partial f_3}{\partial w_1}$) and to investigate longer-term effects of both early life and school-aged wages on adult human capital ($\frac{\partial f_3}{\partial w_1}$ and $\frac{\partial f_3}{\partial w_2}$). In all specifications, we look at lagged effects of rainfall shocks on current outcomes exploiting cohort variation in rain exposure.[15]

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

$$S_{ijhty} = \alpha + \beta\theta_{j,t} + \lambda_h + \phi_t + \psi_y + \epsilon_{ijhty} \tag{2}$$

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. β 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 same district who were born in different cohorts allows us to use household fixed effects in this regression.[16] 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 and/or fertility. Standard errors are clustered at the district level. We

[15] In 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 appendix and show that the main results are similar when we correct for measurement error.

[16] If 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.

discuss potential selection issues in Section 5 below.

Table 5 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 3 ranges from .01-.02, which implies that for each year of exposure to positive rainfall, children score .01-.02 points higher on these tests, and for each year of exposure to drought, they score .01-.02 points lower. 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 .026. 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 0.823. These results are consistent with the idea that both schooling investments and human capital achievement are higher when wages are higher in early life.

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 in Table 6 using IHDS 2004–2005 data.[17] 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

[17]The 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.

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 more likely to not 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 A4-A7).

We find that early life rainfall is associated with both higher early life consumption, and also higher schooling investments and levels of human capital in later childhood. Under the conditions laid out in Proposition 2, these results suggest that there are likely dynamic complementarities between early life and later life human capital investments.

4.3 Long Term Effects of Rainfall Shocks

We are also interested in the effect of total childhood rainfall shocks experienced on adult human capital ($\frac{\partial s_2}{\partial w_1}$ and $\frac{\partial s_2}{\partial w_2}$). Table 3 indicates that students in districts with positive rainfall shocks have lower contemporaneous test scores. 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. In fact, this is what the empirical literature to date suggests (see Jacoby and Skoufias (1997); Funkhouser (1999)). Table 3 suggests that there are lagged effects for rainfall shocks for at least one year, though it's not clear whether these effects will last into adulthood.

To test for this, we estimate Equation 2 using the NSS data on adults (ages 16-30). However, instead of using only early life exposure, we replace $\theta_{j,t}$ with a vector of rain shocks from the in utero period to age 16. Our outcome variable for this specification is total years of schooling. We also use district, rather than household, fixed effects in this specification.

Table 7 indicates that starting at approximately age 4, 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 .23 years). 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 3. 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.

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 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 and/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 cited by (IPCC, 2007) in India, Bangladesh, Mozambique, and even in the USA (Curriero et al., 2001). 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 A9 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 [18]. The results in Table A9 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 A8. The concern is that for whatever health 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, and/or fever. The results indicate that children are actually healthier in positive

[18] Orissa, Chhattisgarh, West Bengal, Jharkhand, and Karnataka (Kumar et al., 2007)

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.[19]. Therefore, we can conclude that children do not appear to be healthier in drought years; rather, the opposite is true.

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 students and 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 ASER School Survey data, and do not find any evidence of this. In fact, column 2 of Table A10 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 and/or schools may have more resources to provide lunches.

5.3 Teacher Attendance

Tables 4 and 2 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 fairly well paid workers, and the

[19]This is despite the fact that incomes are *higher* in positive shock years and *lower* in negative shock years

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.[20]

In column 1 of Table A10 we show the impact of rainfall shocks on teacher attendance 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 cannot be the main driver of the contemporaneous test score results.[21]

5.4 Selective Migration in Contemporaneous Regressions

The primary selection concern for our main results in Table 3 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 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. In a paper titled "Why is Mobility so Low in India?", Munshi and Rosenzweig (2009) using the Rural Economic Development Survey also conclude that rural

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

[21] It is important to note that the school lunch and teacher absence results presented in Table A10 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.

emigration rates are low. Indian Census data from 2001 shows that the inter-district rural migration rate for all ages is .078. However, the rates 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 A12 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. This allows us to test whether individuals are responding to positive and/or negative rainfall shocks by migrating. In columns 2 and 4 we restrict our samples to children ages 5-16. 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 5 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 5, 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 7, 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 2 or 3 "droughts" 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 and/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 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 A11 reports the results of these OLS regressions for 1991 and 2001. All 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 5. 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 Discussion and Conclusion

In this paper we present a simple model of human capital investment, and show that under reasonable conditions, we would expect the effect of wages on human capital investment to be negative when children are school-aged. We also show that, in the presence of strong dynamic complementarities, early life wages will positively affect investment and schooling and overall human capital.

We estimate these comparative statics using test score, schooling, 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.

In addition, we show that the lagged effects of early life positive rainfall shocks on both schooling and human capital are positive. Children who were exposed to droughts in early life score significantly worse on math and reading tests, and are more likely to be behind in school or to never have enrolled. 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.

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.

These 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. This research could inform policy decisions about poverty alleviation programs. Many poverty alleviation programs in the developing world take the form of work programs with inflated wages for agricultural laborers. For example, NREGA in India generated 2.57 billion person days of employment (in 2010-11). If these types of programs raise prevailing wages, they could cause students to substitute toward work and away from for school attendance even if the programs are only in place for adults. Lump sum grants or even 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			
	Mean	Std. Dev.	Observations
Male	.54	.498	2,377,477
Age	10.46	3.15	2,405,642
Math Score	2.63	1.31	2,356,028
Math Score2	1.26	.919	843,827
Reading Score	2.72	1.40	2,368,101
Dropped Out	.037	.188	2,193,040
Never Enrolled	.026	.161	2,405,642
On Track	.823	.381	1,788,427
Rainfall Summary Statistics			
Rain Shock This Year	.148	.631	2,193,040
Rain Shock Last Year	.029	.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 ($\leq$ 18)	.378	.49	473,327
Attends School ($\leq$ 18)	.58	.49	453,160
ln Wages	5.86	0.91	164,597
Total Years of School Ages 16-30	6.21	4.92	306,925
Total Droughts Ages -1 to 16	3.25	1.12	306,925
Total Positive Shocks Ages -1 to 16	3.59	1.23	306,925

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

Table 2: Effect of Rain Shocks on Wages

Effect of Rain Shocks on Wages			
Dependent Variable:	*ln Wages (Age≤18)*	*ln Wages (Females)*	*ln Wages (Males)*
Rain Shock This Year	.09	.07	.02
	(.02)***	(.01)***	(.009)**
Observations	15,038	40,913	108,646
Mean Dependent Variable	5.47	5.42	6.04

Notes: This table shows our estimates of the effect of rain shocks on ln wages using rounds 60, 61, 62, and 64 of NSS data. Rain shock is defined as 1 if rainfall is in the highest quintile, -1 if rainfall is in the lowest quintile, and 0 otherwise. All regressions contain district and age fixed effects. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 3: Effect of Contemporaneous Rainfall Shocks on Human Capital

	Dependent Variable:					
	Math Score	Math Score2	Read Score	Dropped Out	On Track	Attendance
Rain Shock This Year	-.02	-.05	.002	.0002	.003	-.02
	(.01)*	(.02)***	(.01)	(.0008)	(.002)	(.006)***
Rain Shock Last Year	-.02	-.04	-.02	.002	-.010	
	(.01)	(.02)*	(.01)*	(.0009)**	(.003)***	
Observations	2,109,162	843,827	2,120,708	2,193,040	1,687,128	467,606
Mean Dependent Variable	2.62	1.26	2.71	.037	.810	.863

Notes: This table shows our estimates of the effect of rainfall shocks on current test scores. "Math Score" and "Read Score" range from 0-4. "Math Score2" 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. 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 Rain Shocks on Schooling and Child Labor

Effect of Rain Shocks on Working		
Dependent Variable:	*Attends School ($Age \leq 18$)*	*Works ($Age \leq 18$)*
Rain Shock This Year	-.01	.007
	(.002)***	(.001)***
Observations	453,160	473,327
Mean Dependent Variable	.58	.07

Notes: This table shows our estimates of the effect of rain shocks on school attendance and working using rounds 60, 61, 62, and 64 of NSS data. Rain shock is defined as 1 if rainfall is in the highest quintile, -1 if rainfall is in the lowest quintile, and 0 otherwise. All columns restrict the sample to both males and females less than 18 years old. All regressions contain district and age fixed effects. Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 5: Effect of Early Life Rainfall Shocks on Human Capital

	Dependent Variable:				
	Math Score	Math Score2	Read Score	Never Enrolled	On Track
Rain Shock In Utero	.01	.006	.01	-.002	.02
	(.004)***	(.004)	(.004)***	(.0004)***	(.002)***
Rain Shock Year of Birth	.01	.009	.01	-.002	.02
	(.004)***	(.004)**	(.004)**	(.0004)***	(.002)***
Rain Shock at Age 1	.01	.02	.01	-.003	.01
	(.004)***	(.005)***	(.004)***	(.0004)***	(.002)***
Rain Shock at Age 2	.01	.02	.01	-.003	.01
	(.004)**	(.004)***	(.004)***	(.0004)***	(.002)***
Rain Shock at Age 3	.001	.008	.007	-.002	.0003
	(.004)	(.005)*	(.004)	(.0004)***	(.002)
Rain Shock at Age 4	.002	-.008	.01	-.002	.001
	(.004)	(.004)*	(.005)***	(.0004)***	(.002)
Observations	2,356,028	843,827	2,368,101	2,405,642	1,788,427
Mean Dependent Variable	2.63	1.26	2.72	.026	.823

Notes: This table shows our estimates of the effect of early life rainfall shocks on current test scores and schooling outcomes. "Math Score" and "Read Score" range from 0-4. "Math Score 2" 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 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 6: Effect of Rainfall Shocks on Child Weight

	Weight z-score
Rain Shock This Year	.12
	(.05)**
Rain Shock Last Year	.22
	(.06)***
Observations	15,307
Mean Dependent Variable	-1.516

Notes: This table shows our estimates of the effect of rainfall shocks on weight for age z-scores. These are anthropometric z-scores using the 2006 WHO child growth standards. The sample is children ages 1 to 5 in the IHDS 2004–2005 data. 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 7: Effect of Rain Shocks on Total Schooling

Dependent Variable:	Years of Education (NSS data)
In Utero Rain Shock	.01 (.02)
Rain Shock in Year of Birth	-.03 (.02)
Rain Shock at Age 1	-.06 (.03)**
Rain Shock at Age 2	-.03 (.03)
Rain Shock at Age 3	-.11 (.03)***
Rain Shock at Age 4	-.12 (.03)***
Rain Shock at Age 5	-.12 (.03)***
Rain Shock at Age 6	-.05 (.03)*
Rain Shock at Age 7	-.02 (.03)
Rain Shock at Age 8	-.05 (.03)*
Rain Shock at Age 9	-.07 (.03)***
Rain Shock at Age 10	-.13 (.03)***
Rain Shock at Age 11	-.28 (.03)***
Rain Shock at Age 12	-.23 (.03)***
Rain Shock at Age 13	-.28 (.03)***
Rain Shock at Age 14	-.07 (.03)***
Rain Shock at Age 15	-.13 (.03)***
Rain Shock at Age 16	-.04 (.03)*
Mean Dependent Variable	6.04
Observations	306,925

Notes: This table shows our estimates of the effect of childhood rain shocks on total years of schooling using rounds 60, 61, 62, and 64 of the NSS data for individuals 16-30. Rain shock is defined as 1 if rainfall is in the highest quintile, -1 if rainfall is in the lowest quintile, and 0 otherwise. The regressions contain age and district 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 8: Model Predictions and Empirical Results

Source:	Model General	Model Specific	Data Contemporaneous	Data Early Life	Data Long Term
$\frac{\partial s_2}{\partial w_2}$	?	-	-		-
$\frac{\partial f_3}{\partial w_2}$	?	-	-		-
$\frac{\partial s_2}{\partial w_1}$	?	+		+	
$\frac{\partial f_3}{\partial w_1}$	?	+		+	
$\frac{\partial c_1}{\partial w_1}$	+	+		+	

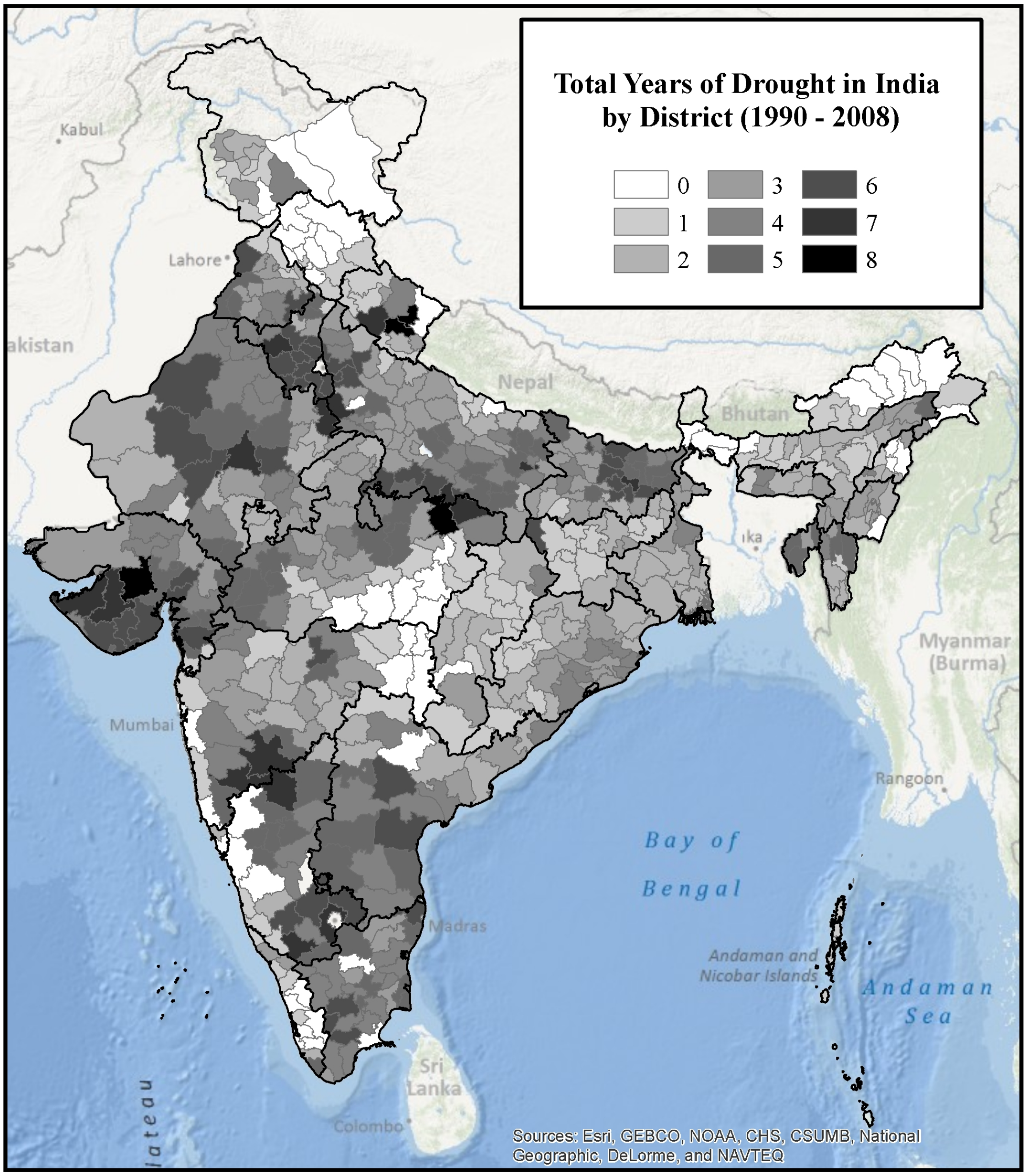

Figure 1: Variation in Drought Across District and Time

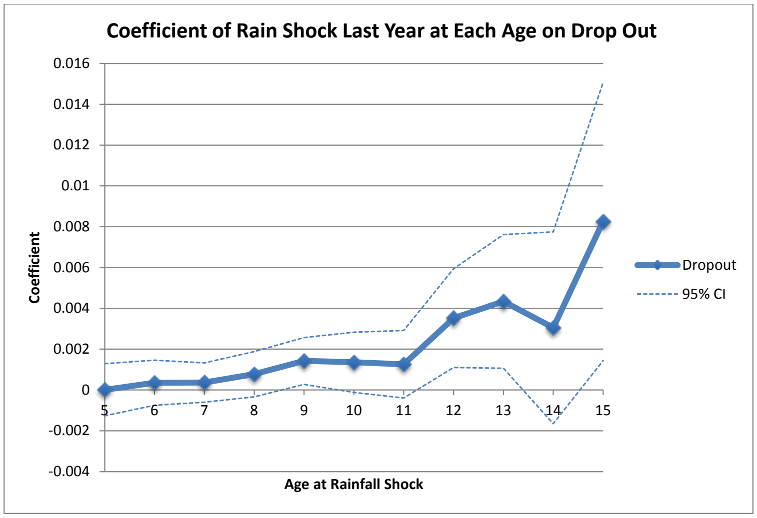

Figure 2: Effect of Rainfall Shocks Last Year on Current Test Scores

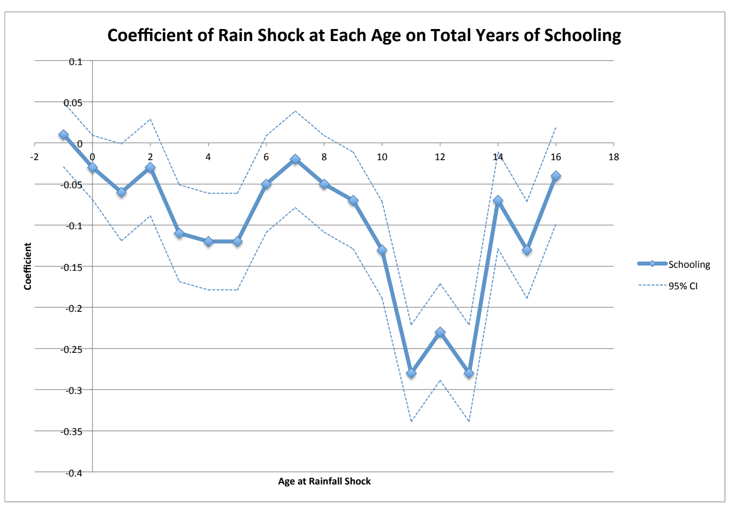

Figure 3: Effect of Rainfall Shocks on Total Years of Schooling

A Appendix Tables

Table A1: Drought and Crop Yields: 1957-1987

	Dependent Variable:					
	Rice		Wheat		Jowar	
Rain Shock	.06 (.02)**	.08 (.02)***	.002 (.01)	.05 (.008)***	.01 (.01)	.02 (.009)***
Year fixed effects	Y	Y	Y	Y	Y	Y
District fixed effects	Y	Y	Y	Y	Y	Y
Controls	Y	N	Y	N	Y	N
Observations	7161	8401	6680	8401	6265	7409
Mean Dependent Variable	1.51	1.51	.856	.856	.589	.589

Notes: This table shows results from a regression of crop yields on rain shocks. 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. An observation is a district-year. Controls are measures of inputs used in production: labor, bullocks, fertilizer, and machinery, as well as 3-year average yield. 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

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

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

	Dependent Variable:		
	Math Score	Math Score2	Read Score
Rain Shock This Year	-.03	-.15	-.002
	(.02)	(.07)**	(.02)
Rain Shock Last Year	-.03	-.15	-.04
	(.02)	(.08)**	(.02)*
Observations	2,109,162	843,827	2,120,708

Notes: This table shows ordered logit estimates of the effect of rainfall shocks on current test scores. "Math Score" and "Read Score" range from 0-4. "Math Score 2" 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 (Boys)

	Dependent Variable:				
	Math Score	Math Score2	Read Score	Dropped Out	Attendance
Rain Shock This Year	-.01	-.05	.003	-.0004	-.02
	(.01)	(.02)***	(.01)	(.0008)	(.006)***
Rain Shock Last Year	-.01	-.04	-.02	.002	-.03
	(.01)	(.02)**	(.01)*	(.0009)**	(.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

Notes: This table shows the effect of rainfall shocks on current test scores for boys. 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 A5: Effect of Contemporaneous Rainfall Shocks on Human Capital (Girls)

	Dependent Variable:				
	Math Score	Math Score2	Read Score	Dropped Out	Attendance
Rain Shock This Year	-.02	-.05	.002	.0008	-.02
	(.01)*	(.02)***	(.01)	(.0008)	(.006)***
Rain Shock Last Year	-.02	-.04	-.02	.002	-.04
	(.01)*	(.02)*	(.01)*	(.0009)**	(.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

Notes: This table shows the effect of rainfall shocks on current test scores for girls. 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 A6: Effect of Early Life Rainfall Shocks on Human Capital (Boys)

	Dependent Variable:				
	Math Score	Math Score2	Read Score	Never Enrolled	On Track
Rain Shock In Utero	.008	.003	.01	-.001	.02
	(.004)*	(.006)	(.005)**	(.0004)***	(.002)***
Rain Shock Year of Birth	.01	.01	.008	-.002	.02
	(.004)**	(.006)*	(.004)*	(.0004)***	(.002)***
Rain Shock at Age 1	.01	.02	.01	-.002	.01
	(.005)**	(.006)***	(.005)**	(.0005)***	(.002)***
Rain Shock at Age 2	.01	.02	.01	-.003	.01
	(.004)***	(.006)***	(.004)***	(.0004)***	(.002)***
Rain Shock at Age 3	.006	.01	.01	-.002	-.0002
	(.005)	(.006)**	(.005)**	(.0004)***	(.002)
Rain Shock at Age 4	.003	-.008	.01	-.002	.002
	(.005)	(.006)	(.005)**	(.0004)***	(.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

Notes: This table shows our estimates of the effect of early life rainfall shocks on current test scores and schooling outcomes for boys. "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 A7: Effect of Early Life Rainfall Shocks on Human Capital (Girls)

	Dependent Variable:				
	maths score	Math Score2	Read Score	Never Enrolled	On Track
Rain Shock in Utero	.02	.009	.02	-.002	.03
	(.005)***	(.006)	(.005)***	(.0006)***	(.003)***
Rain Shock Year of Birth	.01	.005	.01	-.002	.02
	(.005)**	(.007)	(.006)**	(.0006)***	(.003)***
Rain Shock at Age 1	.01	.01	.02	-.003	.02
	(.005)***	(.007)	(.005)***	(.0005)***	(.003)***
Rain Shock at Age 2	.007	.01	.01	-.003	.01
	(.005)	(.007)**	(.005)**	(.0006)***	(.003)***
Rain Shock at Age 3	-.005	-.002	.002	-.001	-.0002
	(.005)	(.007)	(.005)	(.0006)*	(.002)
Rain Shock at Age 4	-.003	-.01	.009	-.002	.0000306
	(.005)	(.007)*	(.005)*	(.0005)***	(.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

Notes: This table shows our estimates of the effect of early life rainfall shocks on current test scores and schooling outcomes for boys. "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 A8: Effect of Rain Shocks on Days Sick and Health Expenditures

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

Notes: This table shows our 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. The sample is children ages 5-16 in the IHDS 2004–2005 data. 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 A9: Effect of Rain Shocks on Test Scores in High Malaria States

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

Notes: This table shows the results of our contemporaneous rainfall specification focusing on the five high malaria states. 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 A10: Are Teacher Absences or School Lunches Driving the Results?

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

Notes: This table shows the effect of rainfall shocks on teacher absence rates and midday meal provision using the 2005 and 2007 ASER School Survey. Rain Shock is defined as -1 if rainfall was below the 20th percentile for the district, 1 if rainfall was above the 80th percentile for the district, and 0 otherwise. 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 A11: Does Drought Impact Fertility Decisions?

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

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 A12: 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	.002		
	(.003)	(.003)		
Drought Last Year	.006	.006		
	(.003)*	(.004)		
Positive Shock This Year			-.003	.007
			(.01)	(.009)
Positive Shock Last Year			.0002	-.001
			(.007)	(.007)
Observations	236,429	67,521	236,429	67,521
Mean Dependent Variable	.987	.987	.987	.987

Notes: These are OLS regressions using NSS round 55 data (1999-2000) where the dependent variable is has not moved from district in past six months or more. In odd numbered columns we use the entire sample and in all even numbered columns we restrict the sample to 5-16 year olds. 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

Effect of School-Aged Wages on Schooling

Parents Solve:

$$\max_{s_2} \left\{ u\left(\alpha w_1 h\right) + \beta u\left(\alpha w_2\left(h + \left(1 - s_2\right) e_2\right)\right) + \beta^2\left(f_3\left(\alpha w_1 h, \alpha w_2 (h + (1 - s_2) e_2), s_2\right)\right)\right\}$$

which yields

$$\text{F.O.C.:} \quad \beta \frac{du}{dc} \alpha w_2 e_2 - \beta^2 \left(\frac{\partial f_3}{\partial s_2} - \frac{\partial f_3}{\partial c_2} \left(\alpha w_2 e_2\right) \right) = 0$$

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

$$\beta \alpha e_2 \left[\frac{d^2 u}{dc^2} w_2 \left(\alpha\left(h + \left(1 - s_2\right) e_2\right) - \alpha w_2 e_2 \frac{\partial s_2}{\partial w_2} \right) + \frac{\partial u}{\partial c} \right] =$$

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

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

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

$$\frac{\partial s_2}{\partial w_2} = \Psi \left(\beta \left[\gamma \left(\frac{\partial^2 f_3}{\partial s_2 \partial c_2} - \alpha e_2 \frac{\partial^2 f_3}{\partial c_2^2} w_2 \right) - \alpha e_2 \frac{\partial f_3}{\partial c_2} \right] - \alpha e_2 \left[\gamma w_2 \frac{d^2 u}{dc^2} + \frac{\partial u}{\partial c} \right] \right)$$

where

$$\Psi(u(c), f_3(e_2, c_2, s_2)) = -\left(\beta \left[\frac{\partial^2 f_3}{\partial s_2^2} - 2\alpha e_2 w_2 \frac{\partial^2 f_3}{\partial c_2 \partial s_2} + \alpha^2 e_2^2 w_2^2 \frac{\partial^2 f_3}{\partial c_2^2} \right] + \alpha^2 e_2^2 w_2^2 \frac{d^2 u}{dc^2} \right)^{-1}$$

and

$$\gamma = \alpha \left(h + (1 - s)\, e_2\right)$$

Proposition 1.

If:

1. *The effect of school aged consumption is relatively small ($\frac{\partial f_3}{\partial c_2} \approx 0$), and*

2. *Income effects are small ($\frac{d^2 u}{dc^2} \approx 0$)*

Then:

$$\frac{\partial s}{\partial w_2} \propto -\alpha e_2 \frac{\partial u}{\partial c} < 0$$

$$\frac{df_3}{dw_2} \approx \frac{\partial f_3}{\partial s_2}\frac{\partial s_2}{\partial w_2} < 0$$

Proof. We know that

$$\frac{\partial s_2}{\partial w_2} = -\Psi \left[\alpha e_2 \frac{\partial u}{\partial c} - \beta \left(\gamma \left(\frac{\partial^2 f_3}{\partial s_2 \partial c_2} - \alpha e_2 \frac{\partial^2 f_3}{\partial c_2^2} w_2\right) - \alpha e_2 \frac{\partial f_3}{\partial c_2}\right) + \alpha e_2 \gamma w_2 \frac{d^2 u}{dc^2}\right]$$

where

$$\gamma = \alpha \left(h + (1 - s)\, e_2\right)$$

and Ψ is the negative inverse of the second order condition.

By assumption, Ψ is positive, so that

$$\frac{\partial s_2}{\partial w_2} \propto -\alpha e_2 \frac{\partial u}{\partial c} + \beta \left(\gamma \left(\frac{\partial^2 f_3}{\partial s_2 \partial c_2} - \alpha e_2 \frac{\partial^2 f_3}{\partial c_2^2} w_2\right) - \alpha e_2 \frac{\partial f_3}{\partial c_2}\right) + \alpha e_2 \gamma w_2 \frac{d^2 u}{dc^2}$$

By condition (1), $\frac{\partial f_3}{\partial c_2} \approx 0$ everywhere, and thus we can write

$$\frac{\partial s_2}{\partial w_2} \propto -\alpha e_2 \frac{\partial u}{\partial c} - \alpha e_2 \gamma \frac{d^2 u}{dc^2}$$

By condition (2), $\frac{d^2 u}{dc^2} \approx 0$

$$\implies \frac{\partial s_2}{\partial w_2} \propto -\alpha e_2 \frac{\partial u}{\partial c} < 0$$

Since α, e_2, $\frac{\partial u}{\partial c} > 0$ by assumption.

Likewise,

$$\frac{df_3}{dw_2} = \gamma \frac{\partial f_3}{\partial c_2} + \frac{\partial f_3}{\partial s_2}\frac{\partial s_2}{\partial w_2} - \alpha e_2 \frac{\partial f_3}{\partial c_2}\frac{\partial s_2}{\partial w_2}$$

By condition (2), $\frac{d^2 u}{dc^2} \approx 0$

$$\implies \frac{df_3}{dw_2} \approx \frac{\partial f_3}{\partial s_2}\frac{\partial s_2}{\partial w_2} < 0$$

$\square$

Effect of Early Life Wages on Schooling

Parents Solve:

$$\max_{s_2} \left\{ u\left(\alpha w_1 h\right) + \beta u\left(\alpha w_2\left(h + \left(1 - s_2\right) e_2\right)\right) + \beta^2 \left(f_3\left(\alpha w_1 h, \alpha w_2 (h + (1 - s_2) e_2), s_2\right)\right) \right\}$$

which yields

$$\text{F.O.C.:} \;\; \beta \frac{du}{dc} \alpha w_2 f_2 - \beta^2 \left(\frac{\partial f_3}{\partial s_2} - \frac{\partial f_3}{\partial c_2} \left(\alpha w_2 f_2\right) \right) = 0$$

Taking the total derivative with respect to period 1 wages yields

$$\beta \alpha w_2 \left[\frac{d^2 u}{dc_2^2} e_2 \left(\alpha w_2 \left((1 - s_2) \frac{df_2}{dc_1} \alpha h - e_2 \frac{\partial s_2}{\partial w_1} \right) \right) + \frac{du}{dc_2} \left(\frac{\partial f_2}{\partial c_1} \alpha h \right) \right] =$$

$$\beta^2 \left[\alpha h \left(\frac{\partial f_3^2}{\partial s_2 \partial c_1} \right) + \frac{\partial f_3^2}{\partial s_2 \partial c_2} \left(\alpha w_2 \left((1 - s_2) \alpha h \frac{\partial f_2}{\partial c_1} - e_2 \frac{\partial s_2}{\partial w_1} \right) \right) + \frac{\partial f_3^2}{\partial s_2^2} \frac{\partial s_2}{\partial w_1} \right]$$

$$-\beta^2 \left[\alpha w_2 \left(\alpha h \left(\frac{\partial f_3^2}{\partial c_2 \partial c_1} \right) + \frac{\partial f_3^2}{\partial c_2^2} \left(\alpha w_2 \left((1 - s_2) \alpha h \frac{\partial f_2}{\partial c_1} - e_2 \frac{\partial s_2}{\partial w_1} \right) \right) + \frac{\partial f_3^2}{\partial c_2 \partial s_2} \frac{\partial s_2}{\partial w_1} \right) e_2 + \frac{\partial f_3}{\partial c_2} \frac{\partial f_2}{\partial c_1} \alpha h \right]$$

Rearranging, we have

$$\frac{\partial s_2}{\partial w_1} = \Psi[\beta\left(\alpha h\left(\frac{\partial f_3^2}{\partial s_2 \partial c_1} - \alpha w_2 e_2 \frac{\partial f_3^2}{\partial c_2 \partial c_1}\right) + \delta\left(\frac{\partial f_3^2}{\partial s_2 \partial c_2} - \alpha w_2 e_2 \frac{\partial f_3^2}{\partial c_2^2}\right)\frac{\partial f_2}{\partial c_1} + \frac{\partial f_3}{\partial c_2}\frac{\partial f_2}{\partial c_1}\alpha h\right)$$

$$-\alpha w_2\left(\lambda \frac{d^2 u}{dc^2}\frac{de_2}{dc_1} + \frac{du}{dc}\frac{\partial f_2}{\partial c_1}\alpha h\right)]$$

where

$$\Psi(u(c), f_3(e_2, c_2, s)) = -\left(\beta\left[\frac{\partial^2 f_3}{\partial s^2} - 2\alpha e_2 w_2 \frac{\partial^2 f_3}{\partial c_2 \partial s} + \alpha^2 e_2^2 w_2^2 \frac{\partial^2 f_3}{\partial c_2^2}\right] + \alpha^2 e_2^2 w_2^2 \frac{d^2 u}{dc^2}\right)^{-1} > 0$$

and

$$\delta = \alpha w_2\left((1 - s_2)\alpha h\right)$$

and

$$\lambda = e_2 \alpha w_2 (1 - s)\alpha h$$

Proposition 2.

If:

1. *The effect of school-aged consumption is relatively small ($\frac{\partial f_3}{\partial c_2} \approx 0$), and*

2. *Income effects are small ($\frac{d^2 u}{dc^2} \approx 0$)*

Then:

$$\frac{\partial s_2}{\partial w_1} \propto \beta \frac{\partial^2 f_3}{\partial s \partial c_1} - \alpha w_2 \frac{\partial u}{\partial c}$$

and thus

$$\frac{\partial s_2}{\partial w_1} > 0 \implies \frac{\partial^2 f_3}{\partial s \partial c_1} > 0$$

Proof. From the F.O.C.,

$$\frac{\partial s_2}{\partial w_1} \propto \beta \left(\alpha h \left(\frac{\partial f_3^2}{\partial s_2 \partial c_1} - \alpha w_2 e_2 \frac{\partial f_3^2}{\partial c_2 \partial c_1} \right) + \delta \left(\frac{\partial f_3^2}{\partial s_2 \partial c_2} - \alpha w_2 e_2 \frac{\partial f_3^2}{\partial c_2^2} \right) \frac{\partial f_2}{\partial c_1} + \frac{\partial f_3}{\partial c_2} \frac{\partial f_2}{\partial c_1} \alpha h \right)$$

$$-\alpha w_2 \left(\lambda \frac{d^2 u}{dc^2} \frac{df_2}{dc_1} + \frac{du}{dc} \frac{\partial f_2}{\partial c_1} \alpha h \right)$$

By condition (1), $\frac{\partial f_3}{\partial c_2} \approx 0$

$$\implies \frac{\partial s_2}{\partial w_1} \propto \beta \alpha h \frac{\partial f_3^2}{\partial s_2 \partial c_1} - \alpha w_2 \left(\lambda \frac{d^2 u}{dc^2} \frac{df_2}{dc_1} + \frac{du}{dc} \frac{\partial f_2}{\partial c_1} \alpha h \right)$$

By condition (2), $\frac{d^2 u}{dc^2} \approx 0$

$$\implies \frac{\partial s_2}{\partial w_1} \approx \beta \alpha h \frac{\partial f_3^2}{\partial s_2 \partial c_1} - \alpha w_2 \frac{du}{dc} \frac{\partial f_2}{\partial c_1} \alpha h$$

$\alpha w_2 \frac{du}{dc} \frac{\partial f_2}{\partial c_1} \alpha h$ is positive by assumption. Thus,

$$\frac{\partial s_2}{\partial w_1} > 0 \implies \frac{\partial^2 f_3}{\partial s \partial c_1} > 0$$

□

Corollary 2. *If:*

1. *Conditions (1) and (2) hold, and*

2. $\frac{\partial s_2}{\partial w_1} > 0$

Then:

$$\frac{df_3}{dw_1} \approx \alpha h \frac{\partial f_3}{\partial c_1} + \frac{\partial f_3}{\partial s}\frac{\partial s}{\partial w_1} > 0$$

Proof. From the human capital production function:

$$\frac{df_3}{dw_1} = \alpha h \frac{\partial f_3}{\partial c_1} + \left((\alpha w_2(1-s)) \frac{\partial f_2}{\partial c_1} \alpha h \right) \frac{\partial f_3}{\partial c_2} - \left(\alpha w_2 e_2 \frac{\partial f_3}{\partial c_2} - \frac{\partial f_3}{\partial s} \right) \frac{\partial s}{\partial w_1}$$

It directly follows that

$$\frac{df_3}{dw_1} \approx \alpha h \frac{\partial f_3}{\partial c_1} + \frac{\partial f_3}{\partial s}\frac{\partial s}{\partial w_1}$$

By condition (2), $\frac{\partial s_2}{\partial w_1} > 0$

$\alpha h \frac{\partial f_3}{\partial c_1}$ is positive by assumption

Thus,

$$\frac{df_3}{dw_1} \approx \alpha h \frac{\partial f_3}{\partial c_1} + \frac{\partial f_3}{\partial s}\frac{\partial s}{\partial w_1} > 0$$

□

Selfish Parents Extension to Model

In the main version of our model, we assume that parents maximize the utility of the child. While this is convenient for us in terms of explication, many papers have shown that this "unitary household" model does not perfectly capture the decision-making of most households. In this section we consider an alternative model, in which parents maximize their own consumption, and some benefit of human capital.

Denote parent's consumption as c_P, which will again be a constant fraction $(1-\alpha)$ of household income. The parent still derives some benefit from the child's human capital, $V_P(e_3)$, which can be thought of in this case as potential remittances.

The Parent Solves:

$$\max_{s_2} \left\{ u\left(c_{P1}\right) + \beta u\left(c_{P2}\right) + \beta^2 \left(V_P\left(e_3\right)\right) \right\}$$

Where now

$$\begin{aligned} c_{P1} =& (1-\alpha) w_1 h \\ c_{P2} =& (1-\alpha) w_2 (h + (1-s_2) e_2) \end{aligned}$$

So we can rewrite the parent's maximization problem as

$$\max_{s_2} \left\{ u\left((1-\alpha) w_1 h\right) + \beta u\left((1-\alpha) w_2 \left(h + \left(1-s_2\right) e_2\right)\right) + \beta^2 \left(V_P\left(e_3\right)\right) \right\}$$

which is exactly analogous to the problem in which parents are maximizing the utility of the child. The key here is the assumption about children consuming a constant fraction of household income. Because of this assumption, it doesn't matter whether parents are maximizing their own consumption or the consumption of their children, because in both cases they simply maximize total household consumption.