NBER WORKING PAPER SERIES

DROUGHT OF OPPORTUNITIES:
CONTEMPORANEOUS AND LONG TERM IMPACTS OF RAINFALL SHOCKS ON HUMAN CAPITAL

Manisha Shah
Bryce Millett Steinberg

Working Paper 19140
http://www.nber.org/papers/w19140

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2013

We would like to thank Marianne Bitler, Kitt Carpenter, Ed Glaeser, Rob Jensen, Larry Katz, Michael Kremer, and Emily Oster for helpful comments. Seminar participants at CMC, CSUF, Harvard, HKUST, NBER Summer Institute, UC Berkeley, UCI, UCSC, USC, and PacDev provided useful feedback. We thank Wilima Wadhwa for generously sharing the ASER data. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Drought of Opportunities: Contemporaneous and Long Term Impacts of Rainfall Shocks on Human Capital
Manisha Shah and Bryce Millett Steinberg
NBER Working Paper No. 19140
June 2013
JEL No. I25,J1,O12

ABSTRACT

Higher wages are generally thought to increase human capital production especially in the developing world. We show that human capital investment is procyclical in early life (in utero to age 3), but then becomes countercyclical. We argue this countercyclical effect is caused by families investing more time in schooling when outside options are worse. We show that children and mothers report a lower likelihood of work in drought years, and children are more likely to attend school. In addition, we find long term impacts of these shocks: adults who experienced more rainfall during school years have lower overall total years of schooling and lower wages. These results suggest that the opportunity cost of schooling, even for fairly young children, is an important factor in determining overall human capital investment.

Manisha Shah
Department of Public Policy
University of California, Los Angeles
Luskin School of Public Affairs
3250 Public Affairs Building
Los Angeles, CA 90095-1656
and NBER
manishashah@ucla.edu

Bryce Millett Steinberg
Harvard University
mmillett@fas.harvard.edu

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 the differential production function of human capital at different ages. Early in life, nutritional inputs and medical care are particularly important, and thus the income effect of wage changes is likely to be more important for human capital production. Later, as time inputs (of both parents and children) become more important in human capital production, the substitution effect may dominate, particularly in contexts with relatively low school fees. A relatively new literature documents that these time intensive investments, particularly early in life, might have long lasting effects (Cunha and Heckman, 2008; Almond and Currie, 2011; Gertler et al., 2012).

In this paper we use rainfall fluctuations in rural India to measure the effect of productivity on human capital investment at *all* ages of a child's life, exploiting fluctuations in monsoon rainfall over time and across districts. Productivity shocks could affect human

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

capital investment through wages in two important ways: by changing total income and by changing the relative price of time. For example, in a drought year, agricultural productivity decreases (especially when agriculture is rainfed), and the relative value of time spent farming decreases. The income effect of this change is straightforward. Families have fewer resources to spend on human capital production, whether this is school fees, books, or proper nutrition. The effect of a drought on time inputs into human capital production is ambiguous. The price of schooling (relative to outside options such as agricultural labor or home production) for children has decreased. This could cause substitution toward human capital production since it has become relatively less expensive. In addition, parents might have more time during drought years to devote to their children's human capital production due to fewer outside opportunities. Since time and income are both important inputs into human capital, the overall effect of drought (and positive rainfall shocks) on human capital attainment is not obvious. The income effect will push human capital investment downward unambiguously in drought years, but the substitution effect could cause households to substitute time toward human capital production.[2]

In our setting, rural India, we posit that the income effect is most likely to dominate during the in utero period, because the time input of parents (and children) is limited during this stage, and nutrition and other prenatal inputs are especially crucial for development.[3] By contrast, the substitution effect will become relatively more important as children age. Primary school is free and compulsory,[4] and the Indian government has built many schools to keep the costs of attendance low. For example, in 1971, 53 percent of villages had a public primary school, in 1991, 73 percent did (Banerjee and Somanathan, 2007), and today

[2]We note the caveat that a drought or positive rainfall shock may result in more than an income and/or substitution effect. For example, drought may also influence the disease environment, relative prices of goods, informal safety nets, access to credit, migration, etc. Later in the paper, we investigate some of these channels as alternative explanations for our results.

[3]Most studies that show long term impacts of the in utero environment attribute findings to Barker's (1994) famous fetal origins hypothesis. The fetal origins hypothesis helps explain why economic and environmental conditions during pregnancy may have long term impacts on health and socioeconomic status (e.g., Almond and Currie (2011); Almond (2006); Almond and Mazumder (2011); Black et al. (2007); Dêschenes et al. (2009); Royer (2009)).

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

almost 100 percent of Indian villages have a primary school (Government of India, 2011). In addition, child labor is still relatively common in rural India, particularly on household farms. Agricultural labor is often traded in spot markets, allowing women and children to work for wages without long term contracts or other extensive margin frictions (Kaur, 2011). While younger children are likely not working as day laborers, they could easily be substituting time in school for labor in the home, either on household plots, or in domestic work (cooking, cleaning, childcare) while older relatives leave the home to work if wages are high.

We test these hypotheses using 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.[5] 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 during drought years, children report higher school attendance and score higher on simple math tests. By contrast, during high rainfall years, children score worse on both math and reading tests, and are more likely to report having dropped out. Using a large, national household labor and employment survey, we corroborate this finding that rural children are less likely to report being enrolled in school when rainfall is higher. For the children in our sample, the substitution effect of higher wages dominates the income effect for human capital investment, and higher rainfall is associated with *lower* test scores and school attainment.

We also estimate the impacts of early life rainfall 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, and children who experience more rain before age 5 are

[5]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.

more likely to be enrolled in school and less likely to be off track in school. Thus, the income effect dominates for these younger children, though the magnitude of the effects on test scores are smaller than the contemporaneous effects.

Lastly, we estimate the long term impacts of droughts and positive rainfall shocks at every age on the oldest children in our sample. We find that for sixteen year olds, both the positive early life effects and negative school age effects are still present. In addition, we look at the effect of rainfall shocks at all ages on schooling and wages for adults aged 16-30 in the labor and employment survey and find similar results for total years of schooling and wages.

Our contribution to this literature is threefold. First, as far as we know, this is the first paper to document the possibility that positive productivity shocks can lead to lower levels of human capital attainment using test scores as the measure of human capital investment. 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 will show that human capital investment is procyclical from the in utero phase to age two, but then becomes counter cyclical. Lastly, we provide new evidence on the long term effects of cumulative shocks on human capital attainment and wages 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 (or EITC in the United States) have become a popular means of redistribution as they provide aid to the poor along with corresponding work incentives.[6] 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.

2 Background and Data

2.1 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 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 on rainfall shocks. In drought years, crop yields are significantly lower regardless of the type of crop. In Section 5.1 we will test explicitly for rainfall's effect on wages and probability of working for both adults and children in rural India.

[6] 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).

2.2 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.[7] 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. The four literacy questions are whether the child can recognize letters, recognize words, read a paragraph, and read a story. In addition, 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 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.

[7] 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`

2.3 Rainfall Data

To determine rainfall shock years and districts, we use monthly rainfall data which is collected by the University of Delaware.[8] 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). Later 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.[9] We also estimate our effects using rainfall quintiles and employing the definition of drought from the Indian Meteorological Department, and none of the results are sensitive to the definition of drought we employ.

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 child cohort variation. Table A3 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.

It is important to note that in general positive rainfall shocks will be good for agricultural output, especially in India where rice cultivation is very important. However, there might also be some cases where positive rainfall shocks are capturing extreme rainfall which

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

[9]These are similar to the definitions employed in Kaur (2011) and Jayachandran (2006).

could have negative consequences for agricultural output. Therefore while negative shocks (i.e. droughts) are always bad for agricultural output, positive rainfall shocks are generally positive but in some cases could have negative impacts on productivity.

2.4 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 and wages.

3 Empirical Strategy

3.1 Contemporaneous Rainfall Shock Regressions

For our primary specification, we take advantage of the quasi-random nature of rainfall shocks within district (and across districts within a year) in order to measure the effect of drought and positive rainfall shocks on test scores. Specifically, we estimate the regression:

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

where S_{ijty} is the test score of student i in district j born in year t and surveyed in year y, $\delta_{j,y}$ is an indicator for whether there was a negative (or positive) rainfall shock in district j in year y, $\delta_{j,y-1}$ is a lagged indicator of the rainfall shock, $\theta_{j,t}$ is a vector of early life rainfall exposure, 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. In this regression we compare children who are surveyed in different years from the same district. Since our regressions contain district level fixed effects, we should not be biased by systematic differences across districts. β_1 is the coefficient of interest and it is the impact of current year drought on the various cognitive test scores. Standard errors are clustered at the district level.

One possible issue with using droughts as quasi-random shocks, is that they may be correlated over time. There are certainly districts in which droughts are more common in all years, but this should not affect our empirical results, since the district fixed effects model uses within district variation in timing of droughts to identify causal effects. However, if it is the case that droughts this year are correlated with droughts next year, then it is difficult to tell the extent to which we are picking up the effects of a single shock or multiple years of rainfall. We test for serial correlation directly in Appendix Table A2. In column 1 we find no significant evidence of serial correlation. In column 2 once we include year fixed effects, the coefficient becomes negative and statistically significant, however, the magnitude of the effect is very small. It is unlikely that such a small amount of negative rainfall correlation will affect our results, particularly because is means that children exposed to a drought this year are *less* likely to have been exposed to a drought last year. Still, we include an indicator for drought (or positive rainfall shock) last year in all regressions.

3.2 Early Life Regressions

We would like to understand the effect of early life rainfall shock on human capital investment, especially since we think the mechanisms might be quite different. However, we only observe test scores for children 5-16. Therefore we look at lagged effects of children who were exposed to drought before age 5 on *current* test scores exploiting cohort variation for all the children.[10] We posit that the effects could last for many years, especially if the channel affecting human capital is nutritional inputs and brain development, and thus we might be

[10] 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. As long as it is not systematically biased, this will only attenuate results.

able to see differences in test scores and other schooling outcomes many years later. We exploit variation in cohorts within district, and use household fixed effects in this specification. 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 test score of student i in district j born in year t and surveyed in year y, who is a member of household h. $\theta_{j,t}$ is a vector of early life rain shocks (as defined above) 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 at each age on test scores. Comparing children from the same district who were born in different cohorts allows us to use household fixed effects in this regression.[11] In addition, 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 discuss potential selection issues in Section 7 below.

We also examine the effect of early life droughts (and positive shocks) on other outcome variables of interest. In these regressions, we estimate Equation 2 above, but we replace S_{ijhty} with schooling outcomes: having never enrolled and being "on track", which is an age for grade variable.[12] We also vary the measure of rainfall, θ in some alternate specifications. We use the Indian Meteorological Department definition of drought and quintiles of rainfall. In addition, we also use a more condensed measure of rainfall, "rain shock" which is equal

[11] 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 (effectively our "control group" in this specification) could be directly affected by their sibling's drought exposure. Regressions estimated with district fixed effects are qualitatively similar, and available upon request.

[12] 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.

to 1 if rainfall is in the top quintile, -1 if rainfall is in the bottom quintile, and 0 otherwise.

3.3 Testing for Longer Term Impacts

We examine the impact of rainfall shocks at all ages on the oldest cohorts (age 16) in our sample. Specifically, we estimate:

$$S_{ijty} = \alpha+\beta_1\nu_{j,t-1}+\beta_2\nu_{j,t}+\beta_3\nu_{j,t+1-t+4}+\beta_4\nu_{j,t+5-t+9}+\beta_5\nu_{j,t+10-t+12}+\beta_6\nu_{j,t+13-t+16}+\gamma_j+\phi_t+\epsilon_{ijty} \quad (3)$$

where S_{ijty} is the test score of student i in district j born in year t and surveyed in year y. $\nu_{j,k}$ is the sum of experienced "rain shocks" (as defined above) for the time period k. That is, $\nu_{j,t-1}$ is rain shocks in the year before birth, and $\nu_{j,t+1-t+5}$ is the sum of the rain shocks from age 2 to age 5.[13] The time periods correspond roughly to schooling periods (in utero, infancy, before primary, lower primary, upper primary and secondary). γ_j is a vector of district fixed effects, ϕ_t is a vector of age effects. In this regression we compare children who are surveyed in different years from the same district. Since our regressions contain district level fixed effects, we should not be biased by systematic differences across districts. β_1-β_6 are the coefficients of interest and they are the impact of rainfall shocks on cognitive test scores at each age. Standard errors are clustered at the district level. In addition, using the NSS data, we estimate Equation 3 replacing S_{ijty} with total years of schooling and log wages for 16-30 year olds.

4 Results

4.1 Results: Contemporaneous Rainfall Shock Exposure

In Table 2 we report our results from Equation 1 estimating the impact of contemporaneous rainfall shocks on test scores. Children who are tested during a drought year in their district

[13] This can be thought of as the number of positive shocks minus the number of droughts during the time period.

score 0.09 points higher on math tests. Since the test is out of 4 points, this can be thought of as about 2.5 points on a test out of 100. In addition, children who experience a current drought are 2 percentage points more likely to have attended school in the previous week (from a mean of 86 percent).

Children who experience a positive shock (higher than the 80th percentile of rainfall for their district), either this year or last year, score .05 points lower on math tests. In addition, these children are more likely to report having dropped out of school in the previous year which is likely one reason their test scores remain lower the year following the positive shock. Figures 2 and 3 show test score effects by age, and the results seem to be fairly consistent across ages. However, Figure 4 shows the effects of positive shocks on dropout by age, which does seem to increase with age, though the estimates are noisy.

We use bottom and top quintiles of rainfall as negative and positive shocks, however, any drought cutoff in rainfall is somewhat arbitrary. In Table A4 we consider alternative measures of rainfall on test scores. The qualitative story here is very similar. Column 1 shows the effect of droughts as defined by the Indian Meteorological Department: 75 percent of the 10 year moving rainfall average. In Column 2, we show the effect of "rain shock", which is defined as 1 if rainfall is in the top quintile, -1 if rainfall is in the bottom quintile, and 0 otherwise. We will use this measure in later specifications in the interest of brevity. Column 3 shows the effect of rainfall in each quintile (relative to the lowest) on test scores; the result here is surprisingly monotonic, even the second quintile is associated with significantly lower test scores than the first. The results are very similar regardless of which measure we employ: more rainfall is associated with lower test scores for children ages 5-16.

4.2 Results: Early Life Rainfall Exposure

Table 3 presents our main estimates of the effect of early life rainfall on test scores and schooling outcomes. Panel A shows the effect of droughts, while Panel B shows the effects of positive rainfall shocks. In the first column, we show the effect of rainfall on math test scores. In general, it looks as though drought exposure under the age of 4 causes a small but statistically significant decrease in math test scores. The largest magnitude is for drought exposure at age 1, which is -.02, or a bit less than one point if the test were out of 100. This is about a third the size of the contemporaneous effect. Drought does not have a statistically significant relationship with reading scores, though the coefficient is negative. The effect of a positive rainfall shock below age 3 is also small (.03) but larger than the effect of the negative shock. More rainfall from in utero to age 2 implies that children score .03 points higher on math and reading tests today. These results suggest that rainfall early in life is positively associated with childhood test scores. This is consistent with the idea that the income effect of the rainfall shocks should dominate at early ages, since nutrition is particularly important, and the children have little margin for substitution. It also indicates that the results of early life shocks are somewhat persistent, at least in the medium term.

In the second two columns, we examine the impact of early life rainfall shocks on schooling outcomes. Early life drought exposure is associated with a higher likelihood of never enrolling in school.[14] For example, experiencing a drought in utero is associated with an 8 percent increase in the likelihood of never enrolling. Magnitudes are similar, but negative, for positive shocks. In the last column, we show the effect of rainfall shocks on being "on track", or age for grade. Children exposed to early life droughts are less likely to be on track, and those exposed to positive rainfall shocks early in life are more likely to be on track. Children exposed to drought in utero are 3 percentage points less likely to be on track, from a mean of 81 percent. In general, the magnitudes for this effect are larger for earlier exposure, and not statistically significant after age 3.

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). The 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

[14] Since some of the children in our sample are quite young, this could also reflect delayed enrollment.

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 differences by gender (results by gender are available upon request).

Much of this literature on early life shock exposure in economics focuses on health outcomes (see Almond and Currie (2011) for a review of literature). However, ASER does not collect information on health outcomes. We turn to another dataset, the National Family Health Survey-2 (NFHS-2), to estimate the effect of in utero drought exposure on health outcomes, which could also effect schooling. We use the 1998-99 NFHS-2 India survey because this is the latest year that district identifiers are publicly available. We merge the rainfall data used above (which is at the district level) to the NFHS-2.[15]

In Table A5, we show the effect of in utero drought on height and weight. In utero drought exposure significantly decreases current height. For example, a child exposed to in utero drought is approximately 6.9 centimeters shorter on average than a similar child born during a non-drought year. This is about a 10 percent decrease and it is statistically significant at .05 level. There are two likely channels through which drought might affect later life achievement. First, maternal nutrition and the in utero environment could have a direct effect on cognitive development, lowering IQ. Second, children exposed to drought could be less healthy overall, and this could impact school attendance. Children who attend less school will most likely have lower test scores. Though we will not be able to distinguish between these channels in this paper, for children in rural India, it is likely that both mechanisms are

[15] The NFHS-2 survey covers a nationally representative sample of more than 90,000 eligible women age 15-49 from 26 states that comprise more than 99 percent of India's population. The survey provides information on fertility, mortality, family planning, and important aspects of nutrition, health, and health care. The NFHS-2 measured children's (ages 0-3) height and weight. Height and weight are a widely used proxy for overall health status and correlate positively with economic outcomes. For example, Case and Paxson (2008) show that height is positively correlated with earnings in the developed world. Similar patterns between height and economics outcomes have been shown for individuals in Brazil (Strauss and Thomas, 1998) and other developing countries (Behrman and Deolalikar, 1989; Deaton, 2008). Similarly, being underweight is correlated with future health problems and worse schooling outcomes.

at play.

4.3 Results: Long Term Effects of Rainfall Shocks

Table 2 indicates that, in general, students in districts with higher rainfall 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 2 suggests that there are lagged effects for positive rainfall shocks, perhaps due to the increased propensity to drop out in these years as well. While most of the children in our sample are simply too young to see long term effects, we employ two strategies to test for possible long term impacts. First, we will look at the effects of rainfall shocks on math scores at each age for the 16 year olds in our sample. While many children are still in school at this age, it will give a sense of the relative importance and lasting effects of rainfall shocks at the various ages (since this is the oldest age in our sample). In addition, we use NSS data for 16-30 year olds to look at the impacts of rainfall at each age on total years of schooling and wages (since most of these individuals will have completed schooling by this age).

In Table 4, we examine the impacts of rainfall at various ages on math scores (in the ASER data) in column 1, and total years of schooling and wages (in the NSS data) in columns 2-3. Rainfall shocks have lasting impacts on math scores when experienced very early in life (in utero) or later in life (early teenage years). A 16 year old who was in utero during a positive rainfall year scores .1 points more than a 16 year old who experienced drought in utero. However, later in life, an 11-13 year old who experiences a positive rainfall shock scores .08 points *lower* than a similar aged child who experienced a drought. These effects are consistent with our earlier findings that early in life, rainfall is good for cognitive test scores, and later in life, it is primarily detrimental. This column indicates that these results persist at least to age 16.

To test for longer term effects, we turn to another dataset, the NSS. While we cannot measure human capital directly in the NSS, we can measure total years of schooling and wages. Interestingly, rainfall shocks experienced at very early ages do not seem to have a long term impact on total years of schooling. For the primary school years, the point estimates are small but statistically significant. However, rainfall shocks experienced between the ages 11 and 16, have a negative and statistically significant impact on total years of schooling. Children complete about .2 more years for every drought experienced during these years, and .2 fewer years for every positive rainfall shock (relative to normal years). That is, a child who experiences a drought in all three years (11-13) will complete a little more than one extra year of schooling relative to a child who experiences positive shocks in all three of those years. The stark difference between the effect in this age range and younger ages is likely due to this age range being the relevant dropout margin. Indeed, in our ASER sample, the median age of dropout is 14, and in Figure 4, it looks as though dropouts during positive rainfall years are larger for this age range. This makes sense, since free primary schooling ends at 8th grade and labor market and marriage opportunities are increasingly relevant for older children. It is important to note that total years of schooling is a crude measure of total human capital, and it is possible that rain shocks at earlier ages also affect long term human capital, but not total years of schooling.

The long term effects on wages are also quite interesting. While the coefficient on rainfall shocks in utero is positive, it is not statistically significant. However, rainfall shocks during primary school years (ages 11-13) have a negative and significant effect on later life wages. One positive rainfall shock year is associated with a 1 percent decrease in wages. It seems likely that this effect is operating through the schooling channel.

Our conceptual framework predicts that the substitution effect will be more likely to dominate in an environment in which school is free. In India, free primary schooling is a relatively recent phenomenon; in 1994, the Government of India started a large push for increased primary schooling, which continued with the Millennium Development Goals and the passage of free and compulsory schooling for all children under 14 in 2009. Thus, it is possible that the effects of rainfall are different for different cohorts within our NSS sample. Figure 5 shows the effect of rainfall shocks at each age on total years of schooling and log wages in the NSS data[16] broken down by three 5 year cohorts: those born 1976-1980, 1981-1985, and 1986-1990. In addition, graphing the three cohorts separately will allow us to be more certain that the observed patterns are being driven by the ages of the individuals at the time of the rainfall shocks, and not, say, a particularly bad drought that hit in one particular year.

The first graph shows the effect of rain shock at each age on years of schooling for each of the three cohorts. The pattern is clear: rainfall is generally good for schooling for the oldest cohort (not surprising, since most of them likely had to pay tuition for primary school), sometimes good and sometimes bad for schooling for the middle cohort, and generally bad for schooling for the youngest cohort. In addition, the age patterns are reasonable– early life rainfall is generally good for schooling and wages, and the substitution effect is strongest for all three cohorts around puberty, when many children drop out of school. The spike upward after age 14 for the youngest cohort is likely due to the fact that free schooling is only guaranteed for all children in India *up to age 14*, and thus, we would expect the income effect to be stronger for students of this age.

The three graphs that follow show the effect of rainfall at each age on total years of schooling as well as log wages for each cohort separately. The patterns are remarkably similar for schooling and wages. Whether the effect of rainfall on later life wages is only driven through its effect on schooling is beyond the scope of this paper, but it seems plausible that the effect of temporary rain shocks at critical ages could have lasting effects on adult wages.

[16]These figures graph the coefficient on the variable "rain shock" at each age against the total years of schooling or log wages in the NSS data. The equation being estimated is similar to Equation 3, except that the shocks are not summed by age group, but estimated separately for each age. All regressions include fixed effects for age and district.

5 Pathways

Weather shocks in rural India are likely to impact rural households primarily through their effect on agricultural production and wages. It is clear from the attendance and dropout results in Table 2 that children are indeed substituting toward schooling in drought years, and away during positive rainfall shock years. The positive impacts of drought on test scores are consistent with a context in which the importance of time inputs into human capital production is relatively high.

In the following sections we will show that children and mothers are more likely to work when rainfall is higher. However, it is possible that rainfall shocks could have other indirect effects on human capital. For example, if teachers also respond to positive agricultural wage shocks, they might be less likely to show up for work. Alternatively, if school lunches are more likely to be provided during drought years, this could provide additional incentives for children to attend school. Lastly, if higher rainfall is associated with higher rates of malaria, children might be healthier during drought years and thus more likely to attend school. We will examine these various pathways below and find they are unlikely to be driving our results.

5.1 Work and Wages

The most likely mechanism driving the contemporaneous test score result is lower wages (due to decreased agricultural productivity) which accompany lower rainfall years. Since wages affect not only income but the price of time, lower wages create a substitution effect, in which the relative price of schooling to the outside option becomes cheaper in low rainfall years. When wages are higher, older children might be more likely to work in the labor market, and younger children could substitute into home production.[17] In addition, higher wages and agricultural productivity could lead parents to be more likely to work, and thus

[17] This work could be agricultural, but need not be. For example, higher wages could drive older relatives out of the home and into the workforce, and young children could be substituting for their labor in chores like cleaning and caring for younger siblings.

less likely to be at home. This could imply less time spent with children, and particularly less time investing in children's human capital. To the extent that both parental and child time are important inputs into children's human capital, both of these channels could cause lower cognitive test scores in years with higher rainfall. In fact, experimental evidence from Jamaica and Colombia illustrates that remarkably simple socio-emotional stimulation to toddlers (of only one hour per week) results in large positive impacts on child ability as well as later life wages (Gertler et al. (2012); Attanasio et al. (2012)).

While some evidence shows that higher rainfall leads to higher agricultural productivity, higher wages, and increased work participation in India (e.g., Jayachandran (2006); Kaur (2011)), there is some evidence to the contrary.[18] Thus, we will test for the average effect of rainfall on work and wages in rural areas for both children and parents in our setting.

Tables 5 show the effect of rainfall shocks on work and wages. In general the results are consistent with rainfall as a productivity shock. In this analysis we replace separate positive and negative rainfall shocks with one variable, "rain shock," which is equal to 1 if rainfall is above the 80th percentile, -1 if rainfall is below the 20th percentile, and 0 otherwise. We do this primarily for reasons of brevity, though it also increases our power. Separate results for positive and negative shocks are qualitatively similar, and available upon request. Panel A of Table 5 shows the effect of rain shocks on probability of working. Consistent with our ASER results, children are less likely to report attending school in years with more rainfall. In addition, children are 20 percent more likely to report working in positive rainfall years relative to droughts. Women also report more work during higher rainfall years, though standard errors become large. Interestingly, men do not report lower likelihood of work during higher rainfall years, though the magnitude of this effect is small

[18] Rose (2001) finds that low rainfall increases labor force participation in rural India. Kochar (1999) also finds that male household member increase hours worked in response to negative crop income shocks. However, Rosenzweig and Wolpin (2000) show that when rainfall levels are higher, while adult family members do work significantly fewer days per year since they hire labor, family time in supervisory activities is actually higher in such areas. The labor supply response to rainfall shocks will most likely depend on whether the household owns land, and if so, how much land. For example, Bar and Basu (2009) show that small increases in land lead to increases in child labor but this relationship switches as the size of landholdings increase.

relative to the mean. Panel B shows the effect of rain shock on wages, which is consistent with the productivity story for children, mothers and fathers, though effect sizes are largest for children and mothers. These results are broadly consistent with the idea that children are substituting school time for work when rainfall, and thus wages, are particularly high. Results for mothers are similar, and since women tend to be primary caregivers, it is likely they are spending less time investing in children's human capital in good rainfall years. These results are consistent with Miller and Urdinola (2010) who find that coffee price reductions are associated with substantial declines in the probability that adults work in Columbia; this leads to reductions in child deaths since parents have more time to invest in the health of their children when world coffee prices are low. Similarly, Atkin (2012) finds that factory openings across Mexican municipalities result in increased school dropout.

5.2 Alternative Explanations?

Teacher Attendance Table 5 illustrates 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 wages that are most affected by rainfall shocks are those for agricultural laborers, who earn very little. The additional wage income available during good years for day labor such as weeding and harvesting is small relative to teacher's salaries.[19]

In Table 6 we show the impact of rainfall shocks on teacher attendance rates recorded by surveyors in the ASER School Survey. The results indicate that if anything, teachers are slightly 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.

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

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 6 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.

It is important to note the caveat that the school lunch and teacher absence results presented in Table 6 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.

Healthier Children During drought years, malaria rates could be lower so children could be healthier and attend school more, explaining the test score results. However, this is controversial; there is also 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, we test for the possibility that differences in malaria infections during drought years might explain the test score results. In Table A6 we re-estimate our contemporaneous shock regressions including an interaction of rainfall shock with malaria state (=1 if Orissa, Chhattisgarh, West Bengal, Jharkhand, or Karnataka as these are the states which contributed the most malaria cases in India) (Kumar et al., 2007). The results in Table A6 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.

6 Heterogeneity Analysis

There are certain circumstances where we might expect the income or substitution effect to dominate. For example, if schooling is costly then income effects could be relatively more important. Indeed, this is already clear from the long term results shown in Figure 5. In poorer areas, we also expect more children to be on the margin between school attendance and work. Below we explore some of these hypotheses.

Income Unfortunately the ASER dataset does not have information on socio-economic status of households. However, in almost every round of the survey we have a measure of mother's schooling. We use this as a proxy for household socioeconomic status. In Panel A of Table 7, we re-estimate Equation 1 with an interaction term for whether the child's mother reported any schooling. The interaction term is positive, and almost completely reverses the overall effect. That is, those children whose mother's reported some schooling are largely unaffected by the rainfall effects, which are concentrated in those children whose mother's had no schooling. This is consistent with poorer children being more affected by rainfall shocks, which is not surprising, since we expect these children to be more likely to be on the margin of missing school or dropping out in order to work in agriculture.

Educational Expenditure Free primary school is provided by the Government of India and such schools are available in every village in India. However, in practice educational expenditures vary widely by region. While educational expenditure is clearly an endogenous choice, some of the variation stems from different policies at the state and district level. We generate mean educational expenditure by district using NSS consumption data from round 62 in Indian rupiah. In Panel B of Table 7 we regress test scores on the interaction between rainfall shock and log school expenditure. Not surprisingly, we find that the overall effect of expenditure increases test scores. The interaction term is positive and significant indicating that in districts where more is spent on education, this mitigates the negative effect of positive rainfall shocks on test scores. At the mean of log expenditure (12.15) the effect size is equal to about 0.5 which basically implies that the effects are being driven by below mean expenditure districts which is exactly as we would expect. These results suggest that families in districts who spend more on education are less likely to respond to rainfall shocks on the schooling margin. This evidence is also consistent with various studies showing schooling costs affect the child labor versus schooling decision (see Edmonds et al. (2007); Edmonds (2008)).

7 Potential Selection Bias Issues

7.1 Selective Migration

The primary selection concern for our main results 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 were leaving their districts permanently when rainfall is particularly high (or low). However, migration rates in rural India are extremely low. For example, Topalova (2005) using data from the National Sample Surveys finds that only 3.6 percent of the rural population in 1999-2000 reported changing districts in the previous 10 years. Munshi and Rosenzweig (2009) using the Rural Economic Development Survey also conclude that rural emigration rates are low. Pathania (2007) using Indian Census data also finds that only a small fraction of rural women reside in districts different from their district of birth. Since it's likely that out-migration happens more often in drought years, and migrants are positively selected, this would attenuate our results (since we are finding children score higher in drought years).

In the long term results, our main finding is that rainfall around the age of late childhood and puberty 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 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.

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.

7.2 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. Rural fathers could migrate during drought years in search of work and their absence would result in delayed fertility. 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 children born in 1991 and 2001. We regress the ln number of children in each cohort by district on measures of drought and ln total population by district. 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 A7 reports the results of these OLS regressions for 1991 and 2001. Most of the coefficients are small, and only two are statistically significant. In column 1, drought in t-3 is significantly (and negatively) correlated with number of births. However, in column 2, drought in t-4 is significantly (and positively) correlated with number of births. 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.

Another piece of evidence which points against selective fertility (and selective migration) are the household fixed effects results of Table 3. 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.

8 Discussion and Conclusion

In this paper we show that under certain circumstances, positive productivity shocks can cause lower investment in human capital. However, the effects differ significantly with the timing of these shocks. Consistent with previous literature, we find that for young children, human capital investment is procyclical. Children who are exposed to drought early in life score significantly worse on literacy and numeracy tests than their peers. These children are less likely to be on track in school and less likely to ever enrol. We argue that the results are causal and not due to differences in the sample of children exposed to these shocks. This is likely due to the fact that, particularly during the infancy and in utero periods, nutrition is an extremely important input into later cognitive ability.

By contrast, human capital investment is countercyclical for school aged children. Children who are tested during a drought year score significantly better on math tests, and report higher attendance rates. In positive rainfall years, the opposite holds true. We argue that the likely explanation lies in the relative paucity of outside options during bad rainfall years, both in the home and in the labor market, leading to increased school attendance. Children on the margin of missing school or dropping out might stay in school if wages are low and outside opportunities are scarce. While we do not have direct time use data for the children in the ASER data set, we show that for similar aged samples in rural areas, the probability of working decreases during droughts, which is consistent with this theory.

It is important to note that these results are likely to hold in a context in which there is sufficient scope to substitute from labor market to human capital time allocation. In particular, a child labor market (or significant home production capacity) is necessary. In addition, low (or no) school fees are important factors for the substitution effect to dominate. Indeed, our long term analysis in Figure 5 illustrates that the effect is primarily for the cohorts young enough to have faced relatively cheap or free primary school. In Panel B of Table 7, we show that the effects are stronger in districts that spend less on schooling, which lends credence to this assertion. However, as with the heterogeneous treatment effects shown in Panel A of Table 7, this is also consistent with poorer children being more likely to be on the margin of school attendance.

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 consider not just fees and tuition, but the opportunity cost of attendance in terms of wages as well.

References

Akresh, Richard, Emilie Bagby, Damien de Walque, and Harounan Kazianga, "Child Ability and Household Human Capital Investment Decisions in Burkina Faso," 2010. IZA Discussion Paper 5326.

Almond, Douglas, "Is the 1918 Influenza Pandemic Over? Long-Term Effects of In Utero Influenza Exposure in the Post-1940 U.S. Population," *Journal of Political Economy*, 2006, *114* (4), 672712.

_ **and Bhashkar Mazumder**, "Health Capital and the Prenatal Environment: The Effect of Ramadan Observance during Pregnancy," *American Economic Journal: Applied Economics*, October 2011, *45* (3), 56–85.

_ **and Janet Currie**, "Killing Me Softly: The Fetal Origins Hypothesis," *Journal of Economic Perspectives*, Summer 2011, *25* (3), 153–172.

ASER, "Annual Status of Education Report (Rural) 2009," Annual Report, Pratham 2010.

Atkin, David, "Endogenous Skill Acquisition and Export Manufacturing in Mexico," July 2012. Working Paper.

Attanasio, Orazio, Emla Fitzsimons, Camila Fernandez, Sally Grantham-McGregor, Costas Meghir, and Marta Rubio-Codina, "Home Visiting in Colombia: Impacts of a Scalable Intervention," 2012.

Banerjee, Abhijit and Rohini Somanathan, "The political economy of public goods: Some evidence from India," *Journal of Development Economics*, 2007, *82*, 287314.

Bar, Talia and Kaushik Basu, "Children, Education, Labor, and Land: In The Long Run and Short Run," *Journal of the European Economic Association*, 04-05 2009, *7* (2-3), 487–497.

Behrman, Jere and Anil Deolalikar, *Causes and implications of seasonal variability in household food security*, The Johns Hopkins University Press, 1989.

Berg, Erlend, Sambit Bhattacharyya, Rajasekhar Durgam, and Manjula Ramachandra, "Can Rural Public Works Affect Agricultural Wages? Evidence from lndia," May 2012. CSAE Working Paper.

Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes, "From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes," *Quarterly Journal of Economics*, 2007, *122* (1), 40939.

Case, Anne and Christina Paxson, "Stature and Status: Height, Ability, and Labor Market Outcomes," *Journal of Political Economy*, June 2008, *116* (3), 499–532.

Chaudhury, Nazmul, Jeffrey Hammer, Michael Kremer, Karthik Muralidharan, and F. Halsey Rogers, "Missing in Action: Teacher and Health Worker Absence in Developing Countries," *Journal of Economic Perspectives*, Winter 2006, *20* (1), 91–116.

Cunha, Flavio and James J. Heckman, "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Journal of Human Resources*, 2008, *43* (4), 738–82.

Deaton, Angus, "Height, Health, and Inequality: The Distribution of Adult Heights in India," *American Economic Review: Papers & Proceedings*, 2008, *98* (2), 468474.

Dêschenes, Olivier, Michael Greenstone, and Jonathan Guryan, "Climate Change and Birth Weight," *American Economic Review Papers & Proceedings*, May 2009, *99* (2), 211–217.

Duryea, Suzanne and Mary Arends-Kuenning, "School Attendance, Child Labor and Local Labor Market Fluctuations in Urban Brazil," *World Development*, 2003, *31* (7), 1165–1178.

Edmonds, E., N. Pavcnik, and P. Topalova, "Trade adjustment and human capital investments: Evidence from Indian tariff reform," 2007. NBER Working paper no. 12884.

Edmonds, Eric, "Child Labor," in Hollis Chenery and T.N. Srinivasan, eds., *Handbook of Development Economics*, Elsevier, 2008.

Funkhouser, Edward, "Cyclical Economic Conditions and School Attendance in Costa Rica," *Economics of Education Review*, 1999, *18* (1), 31–50.

Gertler, Paul, Arianna Zanolini, Rodgrio Pinto, James Heckman, Susan Walker, Christel Vermeersch, Susan Chang, and Sally Grantham-McGregor, "Labor Market Returns to Early Childhood Stimulation: A 20-Year Follow-up to the Jamaica Study," 2012.

Government of India, "Census 2011," 2011.

Haque, Ubydul, Masahiro Hashizume, Gregory E. Glass, Ashraf M. Dewan, Hans J. Overgaard, and Taro Yamamoto, "The Role of Climate Variability in the Spread of Malaria in Bangladeshi Highlands," *PLoS ONE*, 12 2010, *5* (12).

Imbert, Clement and John Papp, "Equilibrium Distributional Impacts of Government Employment Programs: Evidence from Indias Employment Guarantee," March 2012. Paris School of Economics Working Paper.

Jacoby, Hanan G. and Emmanuel Skoufias, "Risk, Financial Markets, and Human Capital in a Developing Country," *The Review of Economic Studies*, July 1997, *64* (3), 311–335.

Jayachandran, Seema, "Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries," *Journal of Political Economy*, 2006, *114* (3).

Jensen, Robert, "Agricultural Volatility and Investments in Children," *The American Economic Review*, May 2000, *90* (2), 399–404.

Kaur, Supreet, "Nominal Wage Rigidity in Village Labor Markets," 2011. Harvard University Working Paper.

Kochar, Anjini, "Smoothing Consumption by Smoothing Income: Hours-of-Work Responses to Idiosyncratic Agricultural Shocks in Rural India," *The Review of Economics and Statistics*, 1999, *81* (1), 50–61.

Kruger, Diana, "Coffee production effects on child labor and schooling in rural Brazil," *Journal of Development Economics*, 2007, *82*, 448463.

Kumar, Ashwani, Neena Valecha, Tanu Jain, and Aditya P. Dash, "Burden of Malaria in India: Retrospective and Prospective View," *American Journal of Tropical Medicine and Hygiene*, 2007, *77*, 6978.

Maccini, Sharon and Dean Yang, "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall," *American Economic Review*, June 2009, *99* (3), 1006–26.

Mahajan, Vijay and Rajeev Kumar Gupta, "Non Farm Opportunities for Smallholder Agriculture," January 2011. Paper presented at the IFAD Conference on New Directions for Smallholder Agriculture.

Mankiw, N. Gregory, David Romer, and David N. Weil, "A Contribution to the Empirics of Economic Growth," *The Quarterly Journal of Economics*, 1992, *107* (2), pp. 407–437.

Miller, Grant and B. Piedad Urdinola, "Cyclicality, Mortality, and the Value of Time: The Case of Coffee Price Fluctuations and Child Survival in Colombia," *Journal of Political Economy*, 2010, *118* (1).

Munshi, Kaivan and Mark Rosenzweig, "Why is Mobility in India so Low? Social Insurance, Inequality and Growth," 2009. NBER Working Paper No. 14850.

Pathania, Vikram, "The Long Run Impact of Drought at Birth on Height of Women in Rural India," November 2007. Working Paper.

Rao, C. H. Hanumantha, Susanta K. Ray, and K. Subbarao, *Unstable Agriculture and Droughts : Implications for Policy*, New Delhi: Vikas Publishing House, 1988.

Rose, Elaina, "Ex ante and ex post labor supply response to risk in a low-income area," *Journal of Development Economics*, April 2001, *64* (2), 371–388.

Rosenzweig, Mark and Robert Evenson, "Fertility, Schooling, and the Economic Contribution of Children in Rural India: An Econometric Analysis," *Econometrica*, July 1977, *45* (5), 1065–1079.

Rosenzweig, Mark R. and Kenneth I. Wolpin, "Natural "Natural Experiments" in Economics," *Journal of Economic Literature*, December 2000, *38* (4), 827–874.

Royer, Heather, "Separated at Girth: US Twin Estimates of the Effects of Birth Weight," *American Economic Journal: Applied Economics*, 2009, *1* (1), 49–85.

Schady, Norbert, "Do Macroeconomic Crises Always Slow Human Capital Accumulation?," *World Bank Economic Review*, 2004, *18* (2), 131–154.

Singh, Abhijeet, Albert Park, and Stefan Dercon, "School Meals as a Safety Net: An Evaluation of the Midday Meal Scheme in India," *Economic Development and Cultural Change*, forthcoming.

Strauss, John and Duncan Thomas, "Health, Nutrition and Economic Development," *Journal of Economic Literature*, June 1998, *36* (2), 766–817.

Thomas, Duncan, Kathleen Beegle, Elizabeth Frankenberg, Bondan Sikoki, John Strauss, and Graciela Teruel, "Education in a Crisis," *Journal of Development Economics*, 2004, *74* (1), 53–85.

Topalova, Petia, "Trade Liberalization, Poverty, and Inequality: Evidence from Indian Districts," 2005. NBER Working Paper No. 11614.

Table 1: Summary Statistics

	Mean	Std. Dev.	Observations
ASER Summary Statistics			
Male	.54	.498	2,699,301
Age	10.3	3.62	2,709,461
Grade	4.64	2.85	2,509,008
Math Score	2.19	1.35	2,489,307
Reading Score	2.71	1.41	2,729,313
Dropped Out	.032	.187	2,678,508
Never Enrolled	.028	.165	2,678,508
On Track	.82	.390	2,038,737
Mother Has Any Schooling	.458	.499	2,317,973
Rainfall Summary Statistics			
Contemporaneous Drought	.134	.367	2,131,761
Contemporaneous Positive Shock	.241	.426	2,131,761
Drought at Birth	.171	.383	2,681,653
Positive Shock at Birth	.123	.328	2,681,653
NSS Outcomes			
Works	.378	.49	1,080,276
Attends School	.58	.49	453,160
ln Wages	5.86	0.91	153,088

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

Table 2: Effect of Contemporaneous Rainfall Shocks on Human Capital

Panel A: Droughts				
	Dependent Variable:			
	Math Score	Read Score	Dropped Out	Attendance
Drought This Year	.09	-.01	.001	.02
	(.02)***	(.02)	(.001)	(.01)**
Drought Last Year	.02	.01	-.002	
	(.02)	(.02)	(.001)	
Observations	1,892,741	2,115,547	2,193,040	470,365
Panel B: Positive Shocks				
	Dependent Variable:			
	Math Score	Read Score	Dropped Out	Attendance
Positive Shock This Year	-.05	-.01	.002	-.004
	(.01)***	(.01)	(.001)	(.008)
Positive Shock Last Year	-.05	-.06	.003	
	(.02)***	(.02)***	(.001)**	
Observations	1,892,741	2,115,547	2,193,040	470,365
Mean Dependent Variable	2.07	2.69	.036	.863

Notes: This table shows our estimates of the effect of positive and negative rainfall shocks on current test scores. Positive and negative shocks are defined as rainfall above the 80th percentile and below the 20th percentile of district rainfall respectively. Columns 1, 2 and 3 contain fixed effects for district, year and age. Since attendance is only observed in 2008, column 4 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 3: Effect of Early Life Rainfall Shocks on Human Capital

Panel A: Droughts

	Dependent Variable:			
	Math Score	Read Score	Never Enrolled	On Track
Drought In Utero	-.01	-.006	.002	-.03
	(.006)*	(.007)	(.0006)***	(.004)***
Drought in Year of Birth	-.01	.001	.002	-.02
	(.006)**	(.007)	(.0006)***	(.003)***
Drought at Age 1	-.02	-.008	.003	-.01
	(.006)**	(.007)	(.0006)***	(.003)***
Drought at Age 2	-.01	-.005	.003	-.006
	(.006)	(.007)	(.0006)***	(.003)**
Drought at Age 3	-.001	.0001	.002	.006
	(.007)	(.007)	(.0006)***	(.003) **
Drought at Age 4	.006	-.005	.002	.006
	(.006)	(.007)	(.0006)***	(.003) **
Observations	2,223,078	2,368,101	2,405,642	1,788,427

Panel B: Positive Rainfall Shocks

	Dependent Variable:			
	Math Score	Read Score	Never Enrolled	On Track
Positive Shock In Utero	.03	.03	-.002	.03
	(.007)***	(.007)***	(.0006)***	(.003)***
Positive Shock in Year of Birth	.03	.03	-.003	.03
	(.007)***	(.007)***	(.0007)***	(.004)***
Positive Shock at Age 1	.03	.03	-.003	.02
	(.007)***	(.007)***	(.0007)***	(.004)***
Positive Shock at Age 2	.02	.03	-.004	.02
	(.007)***	(.007)***	(.0007)***	(.004)***
Positive Shock at Age 3	-.007	.02	-.002	.01
	(.007)	(.007)***	(.0007)***	(.004)***
Positive Shock at Age 4	-.01	.03	-.004	.02
	(.007)*	(.007)***	(.0007)***	(.004)***
Observations	2,223,078	2,368,101	2,405,642	1,788,427
Mean Dependent Variable	2.19	2.70	.027	.821

Notes: This table shows our estimates of the effect of early life rainfall shocks on current test scores and schooling outcomes. Positive and negative shocks are defined as rainfall above the 80th percentile and below the 20th percentile of district rainfall respectively. "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 4: Effect of Cumulative Rain Shocks on Total Schooling and Later-Life Wages

Dependent Variable:	Math Score (ASER data)	Years of Education (NSS data)	ln Wages (NSS data)
In Utero Rain Shock	.05	.02	.004
	(.02)***	(.02)	(.005)
Total Rain Shocks (Birth–Age 1)	-.003	-.03	.001
	(.02)	(.02)	(.005)
Total Rain Shocks (Ages 2–5)	-.001	-.07	-.003
	(.02)	(.02)***	(.004)
Total Rain Shocks (Ages 6–10)	.005	-.06	-.009
	(.02)	(.02)**	(.004)**
Total Rain Shocks (Ages 11-13)	-.04	-.2	-.01
	(.02)**	(.02)***	(.004)***
Total Rain Shocks (Ages 14–16)	-.02	-.13	-.005
	(.02)	(.02)***	(.004)
Mean Dependent Variable	2.99	4.58	5.86
Observations	96,404	306,925	62,115

Notes: This table shows our estimates of the effect of childhood rain shocks on math scores for 16 year olds using ASER data (column 1) and total years of schooling (column 2) and ln wages (column 3) 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 independent variables are the sum of total rain shocks in each age bin. NSS 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 5: Effect of Rain Shocks on Labor Force Participation and Wages

Panel A: Effect of Rain Shocks on Working

Dependent Variable:	*Attends School (Age ≤ 18)*	*Works (Age ≤ 18)*	*Works (Females)*	*Works (Males)*
Rain shock	-.01	.007	.008	-.02
	(.002)***	(.001)***	(.005)*	(.003)***
Rain shock lagged	-.003	.003	-.005	-.01
	(.002)	(.001)**	(.005)	(.002)***
Observations	453,160	473,327	371,280	378,862
Mean Dependent Variable	.58	.07	.34	.79

Panel B: Effect of Rain Shocks on Wages

Dependent Variable:	*ln Wages (Age≤18)*	*ln Wages (Females)*	*ln Wages (Males)*
Rain shock	.09	.07	.02
	(.02)***	(.01)***	(.009)**
Rain shock lagged	.1	.13	.03
	(.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 school attendance (panel A), working (panel A), and ln wages (panel b) 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. In Panel A, columns 1-2 restrict the sample to both males and females less than 18 years old, column 3 to adult females with children in the household, and column 4 to adult males with children in the household. 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 6: 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 lagged	.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 7: Heterogeneous Treatment Effects

Panel A: Effect of Rain Shocks on Test Scores, Mother's Schooling Interaction				
	Dependent Variable:			
	Math Score	Reading Score	Dropped Out	Attendance
Rain shock	-.07	.01	.002	-.007
	(.01)***	(.01)	(.001)**	(.006)
Rain shock*Mother's Schooling	.05	-.007	-.002	.006
	(.009)***	(.009)	(.0009)**	(.003)*
Mother's Schooling	.27	.33	-.03	.03
	(.007)***	(.008)***	(.0008)***	(.002)***
Rain Shock Last Year	-.04	-.04	.001	
	(.01)***	(.01)***	(.0009)	
Observations	1,605,242	1,741,883	1,772,954	446,165
Mean Dependent Variable	2.07	2.69	.036	.863

Panel B: Effect of Rain Shocks on Test Scores, Schooling Expenditure Interaction				
	Dependent Variable:			
	Math Score	Reading Score	Dropped Out	Attendance
Rain shock	-.68	-.59	.02	-.21
	(.17)***	(.21)***	(.02)	(.1)**
Log Expenditure*Rain shock	.05	.05	-.001	.02
	(.01)***	(.02)***	(.001)	(.008)*
Log Expenditure(Rs)	.05	.06	-.006	.02
	(.02)***	(.02)***	(.001)***	(.005)***
Rain shock lagged	.03	.02	.002	
	(.01)**	(.01)	(.0009)*	
Observations	1,845,482	2,063,200	2,137,769	454,245
Mean Dependent Variable	2.07	2.69	.036	.863

Notes: This table shows the effect of rainfall on current year schooling, interacted with measures of household income and schooling expenditure. Panel A shows the main results interacted with mother's schooling. This variable is equal to 1 if the child's mother reported having any schooling, and 0 otherwise. The mean of mother's schooling is .453 and the standard deviation is .498. Panel B shows the main results interacted with the log of household expenditure on education, at the district level, from the NSS in 2005. The mean of log expenditure (in rupees) is 12.2 and the standard deviation is .794. 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. Columns 1, 2 and 3 contain fixed effects for district, year and age. Since attendance is only observed in 2008, column 4 contains fixed effects for state, year, and age. All columns contain controls for early life rainfall (in utero to age 4). Standard errors, clustered at the district level, are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level. All specifications are clustered at the district level. Standard errors are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

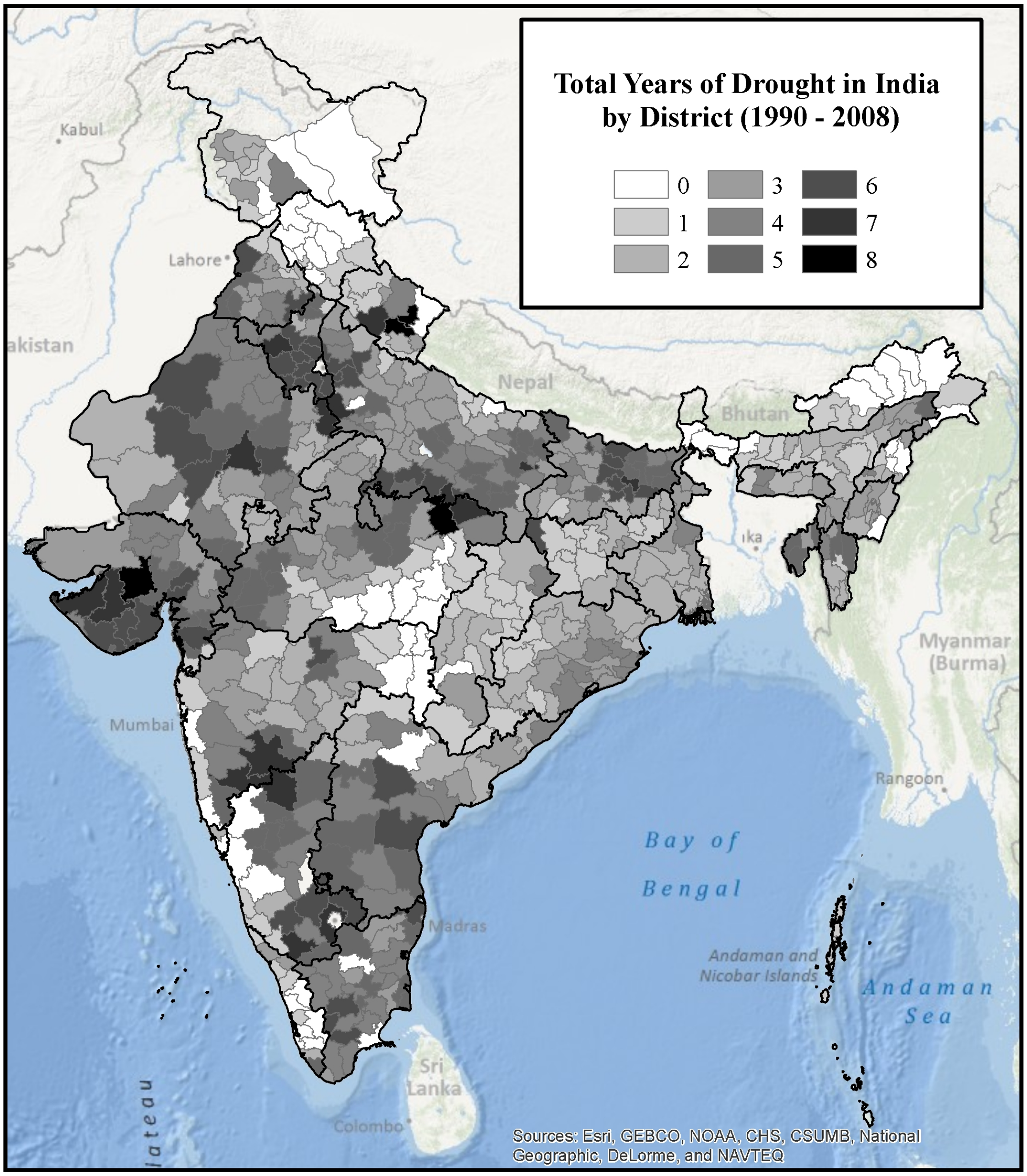

Figure 1: Variation in Drought Across District and Time

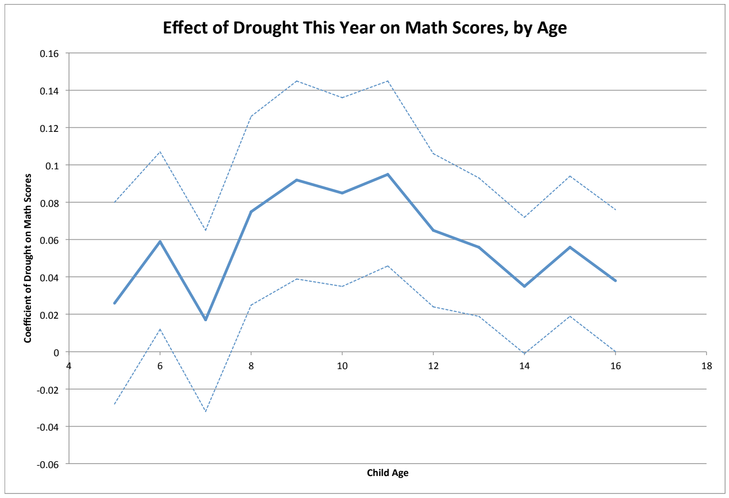

Figure 2: Effect of Negative Shocks on Current Test Scores

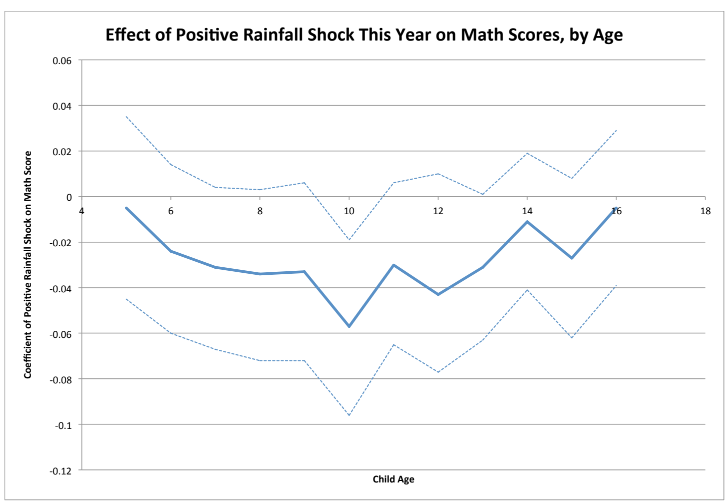

Figure 3: Effect of Positive Shocks on Current Test Scores

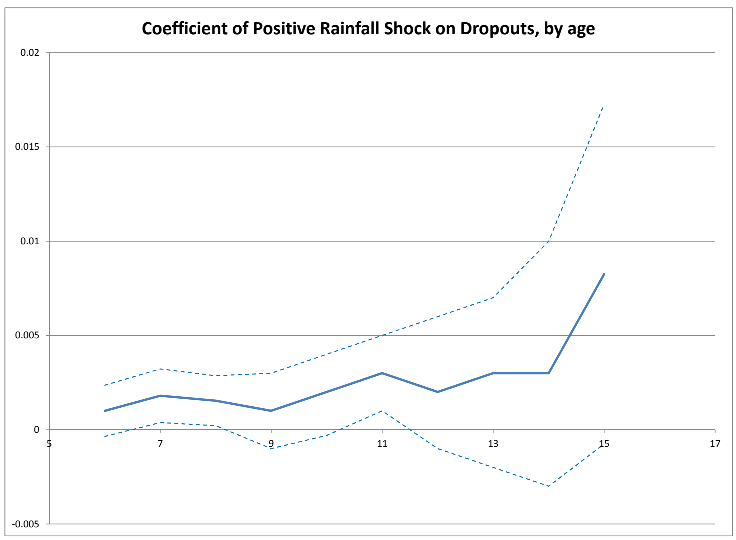

Figure 4: Effect of Positive Shocks on Current Test Scores

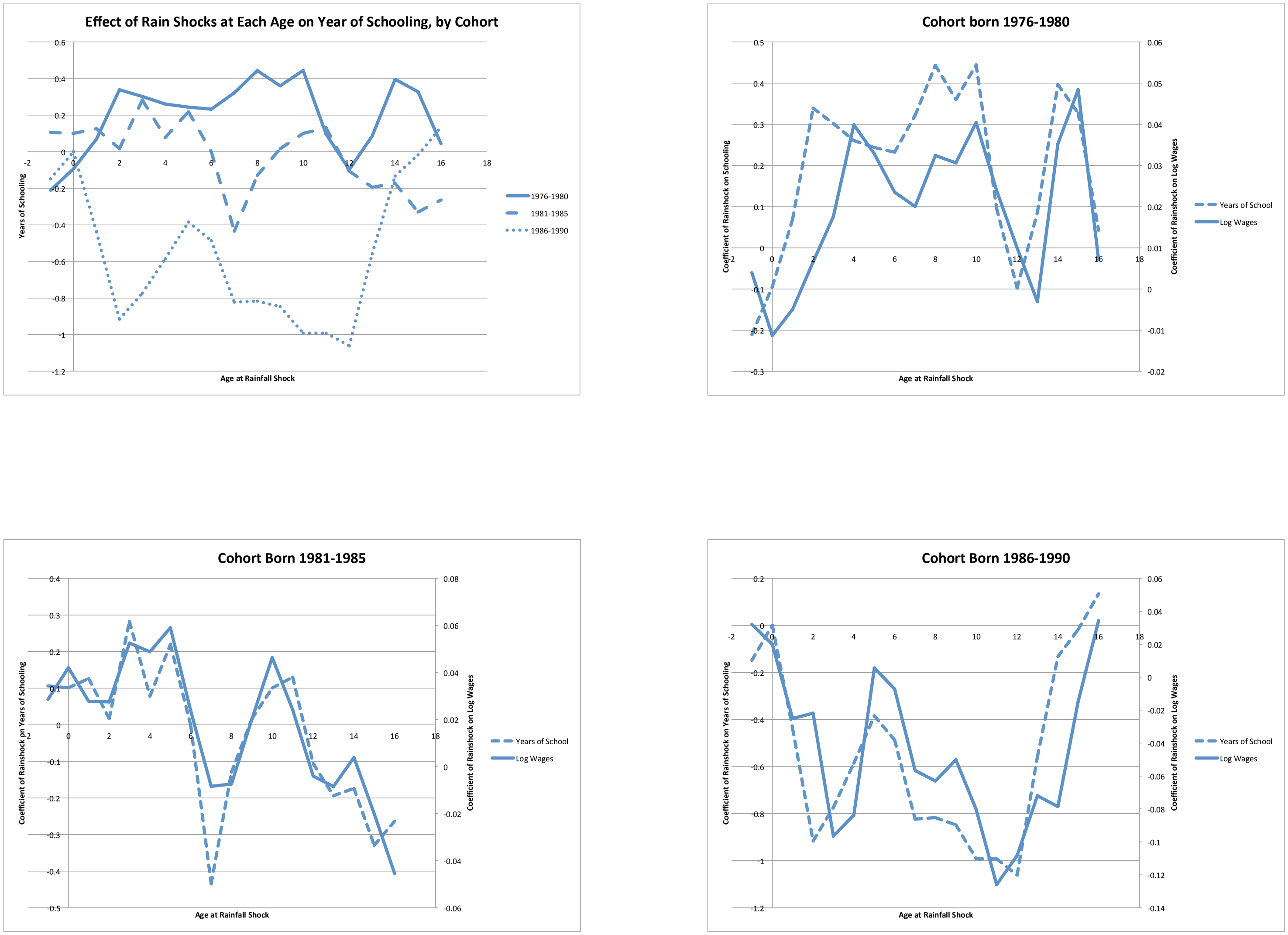

Figure 5: Effect of Rainfall at Each Age on Years of Schooling and Wages, by Cohort

A Appendix Tables

Table A1: Drought and Crop Yields: 1957-1987

	Dependent Variable:					
	Rice		Wheat		Jowar	
Drought	-.41 (.04)***	-.32 (.04)***	-.14 (.02)***	-.16 (.02)***	-.09 (.02)***	-.16 (.03)***
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 tests if crop yields react to drought using the World Bank India Agriculture and Climate Data set which has agricultural yield (revenues per acre) data from 1957-1987. Controls include inputs such as fertilizer, machinery, etc. Standard errors are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A2: Testing for Serial Correlation in Rainfall

Dependent Variable: Deviation from district mean this year		
	(1)	(2)
Deviation from district mean last year	.005	-.031***
	(.011)	(.010)
Year Fixed Effects	N	Y
Observations	9,248	9,248

Notes: This table tests if there is serial correlation in rainfall in our data. An observation is a district year. The dependent variable in both regressions is the deviation from mean rainfall in the current year (in inches), where deviation is simply defined as current year rainfall minus the mean rainfall in sample period. The independent variable is deviation from mean rainfall last year (in inches), constructed in the same way. The mean of the deviation is 0 (2.2e-06)and the standard deviation is 223 inches. Standard errors are reported in parentheses. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table A3: 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 estimates of the percent of districts each year that experience a drought and positive rainfall shock.

Table A4: Alternative Measures of Rainfall

	Dependent Variable: Math Score		
	(1)	(2)	(3)
IMD Drought	.115		
	(.020)***		
Rain Shock		-.054	
		(.01)***	
Bottom Quintile Rainfall			-
Second Quintile Rainfall			-.069
			(.02)***
Third Quintile Rainfall			-.077
			(.02)***
Fourth Quintile Rainfall			-.12
			(.02)***
Highest Quintile Rainfall			-.12
			(.002)***
Observations	1,892,741	1,900,357	1,892,741

Notes: This table shows our estimates of the effect of three different measures of rainfall on math test scores. Rainfall is measured in millimeters: the mean is 1,286 mm and the standard deviation is 788.5 mm. Quintiles of rainfall are measured relative to the entire period of our data rainfall data (1976-2008). IMD Drought is drought as defined by the Indian Meterological Department: less than 75% of a 10 year moving average of district level rainfall. Rain shock is defined as 1 if rainfall is in the highest quintile, -1 if rainfall is in the lowest quintile, and 0 otherwise. In column3, the independent variables are quintiles of rainfall, run as separate dummy variables, in one regression with the bottom quintile omitted. All specifications include district, age, and year of survey 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 A5: Effect of In Utero Drought on Child Health Outcomes

	Dependent Variable	
	Height (cm)	Weight (kilos)
In Utero Drought	-6.89	-.80
	(3.39)**	(.62)
Observations	18,283	18,283
Mean Dependent Variable	71.7	8.17

Notes: This table shows our estimates of the effect of drought in utero on health outcomes. The sample is children 3 and under in the NFHS data set. All regressions contain year of birth and state fixed effects. Children are marked as having a drought occur while in utero if rainfall was below 75% of a 10 year moving average by district in the year prior to their birth (calculated as survey year minus reported age). 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 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 lagged	.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 A7: Does Drought Impact Fertility Decisions?

	ln cohort size (born 1991) (1)	ln cohort size (born 2001) (2)
Drought (t)	.02	-.007
	(.03)	(.02)
Drought In utero (t-1)	-.06	.01
	(.04)	(.03)
Drought (t-2)	-.03	-.02
	(.03)	(.02)
Drought (t-3)	-.12	-.03
	(.06)**	(.04)
Drought (t-4)	-.04	.11
	(.02)	(.02)***
Drought (t-5)	-.04	-.03
	(.03)	(.03)
ln Population 1991	.04	
	(.02)**	
ln Population 2001		.02
		(.02)
Observations	104,630	207,905
Mean Dependent Variable	5.33	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.