Student Paper

Young Lives

Thirsty for Work: The Impact of Early Life Rainfall Shocks on Employment Outcomes in Ethiopia

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The data used come from Young Lives, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (in the states of Andhra Pradesh and Telangana), Peru and Vietnam over a 15-year period. www.younglives.org.uk

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Abstract

Human capital formation plays an important role in economic growth and development. However, developing economies are regularly subjected to a variety of natural disasters that can have prolonged adverse effects on this process. This paper estimates the effects of rainfall shocks exposure during childhood on both educational attainment and employment outcomes in Ethiopia. Using a panel dataset from Ethiopia, I explore two separate questions – how rainfall shocks impact human capital investment in childhood (measured by education) and how these same shocks affect eventual labour market outcomes. I find that positive rainfall shocks at different life stages all result in greater educational attainment. Additionally, I find that increased human capital accumulation reduces the probability that an individual is involved in work in late adolescence, but has no discernible effect on the probability of self-employment. This points towards a premium being placed on greater human capital in the labour market. I also verify whether other factors associated with varied rainfall might be driving the results and find that the primary results remain robust. Finally, I find evidence of non-linear effects when controlling for heterogeneity in shock severity, indicating the need for additional research to be conducted. Based on a model of human capital accumulation, these results suggest that parents in Ethiopia prefer to reinforce the effect of a shock, implying that there is low substitutability between investments across periods. This points to the need to ensure that policies are designed so as to insulate vulnerable communities from the effects of shocks and leave the process of human capital formation unfettered.

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1 Introduction

Ethiopia has a history of being subjected to a variety of natural disasters that result in severe stresses on the communities they affect. Losses in income and changes in consumption arise as a result of these environmental shocks and bring about a broad range of consequences (Berhane, Abay & Woldehanna, 2015). There is a growing literature on the welfare effects of these shocks, as well as possible long-term outcomes for the individuals within the affected communities – particularly in terms of child health, nutrition and cognition (Berhane et al., 2015; Boyden & Dercon, 2012; Woldehanna & Hagos, 2015). Strikingly, individuals younger than 36 months exposed to the 1984-1985 Ethiopian famine were found to be around 3cm shorter than expected at ages 17-25 (Dercon & Porter, 2014). Moreover, evidence from Ecuador indicates that children exposed to food shocks while in utero during the 1997-1998 *El Niño* were more likely to be stunted and to perform worse on vocabulary tests (Rosales, 2014). Thus, exposure to early life shocks can have serious implications for human capital development. Seldom documented, however, is whether the effects of these shocks are severe enough to have a prolonged and persistent effect on human capital development such that eventual labour market outcomes in late adolescence are affected.

More generally, human capital formation is important in both a microeconomic and a macroeconomic context. On the individual level, there is a large literature and body of evidence indicating the positive relationship between increased human capital formation and better socioeconomic outcomes later in life (Currie, 2009; Almond & Currie, 2011a). At an aggregate level, human capital investment is found to be a key driver of economic growth and has important implications for human development in developing countries (Mankiw et al., 1992; Todaro & Smith, 2012). Thus, processes impacting its formation warrant careful study.

In this paper, I use Rounds 1, 2 and 4 of the Young Lives survey's Ethiopian Older Child cohort to explore the link between labour market outcomes at age 19 and early childhood experiences and ability. To highlight the effect that human capital formation may have on these outcomes, I use the impact of early life rainfall shocks on education using data from the African Flood and Drought Monitor (AFDM). I start by exploring how education is affected by rainfall shocks. Following this, I examine the effect of these same shocks on employment outcomes in late adolescence. These two separate questions are linked through the impact of education on employment outcomes. While previous papers focus on the effects of rainfall on human capital formation and educational attainment (Shah & Steinberg, 2015), this paper's ultimate concern is a range of labour market outcomes in late adolescence. The reasons for this are twofold. Firstly, youth unemployment is a growing concern in Ethiopia (Broussar & Tekleselassie, 2012; Guarcello & Rosati, 2007). Secondly, the availability of preliminary labour market outcomes in the fourth round of the Young Lives survey allows for the extension of previous research questions posed (Berhane et al., 2015; Woldehanna & Hagos, 2015).

I focus on rainfall shocks for three reasons. Firstly, Ethiopia relies heavily on rainfed agriculture – thus, these quasi-random shocks affect many Ethiopians' livelihoods. Understanding the impacts that these shocks may have on human capital accumulation and labour market outcomes is therefore important. Rainfall can matter directly through the availability of food or, alternatively, it can be used as a proxy for agricultural wages, since positive rainfall shocks result in greater productivity. This highlights a potential mechanism through which rainfall affects education as a result of the trade-off between educational investment and work (Shah & Steinberg, 2015). Finally, the availability of reliable rainfall data predating the start of the Young Lives sampling process allows the effects of early life rainfall shocks to be observed. This is in contrast to using the self-reported measures of household shocks included in the Young Lives data.

Overall, this paper contributes to three interrelated strands of literature. The first strand is the broader literature on the early childhood influences of socioeconomic outcomes in later life. The second strand is that dealing with childhood work and human capital development. Notably, Woldehanna and Gebremedhin (2015) explore these questions using the Young Lives Ethiopian dataset, while Guarcello and Rosati (2007) make use of the 2001 Ethiopia

Labor Force Survey to examine the labour market outcomes of Ethiopian youth. This relationship is also studied in Vietnam (Beegle, Dehejia & Gatti, 2009) and in Guatemala (Guarcello, Mealli & Rosati, 2010). The third strand is that dealing with the effect of shocks experienced during childhood on future outcomes. For example, Berhane et al. (2015) look at cognitive outcomes specifically and also use the Ethiopian Young Lives data. Outside Ethiopia, evidence from rural India shows how shocks can induce labour market decisions to change (Kochar, 1999). From a cross-country perspective, the impact of natural disasters is found to reduce educational attainment more severely in developing countries (Toya & Skidmore, 2007).

The paper makes some relevant additions to the literature. Unlike previous studies, this paper does not consider the impact of shocks using self-reported data (Berhane et al., 2015; Woldehanna & Gebremedhin, 2015). Instead, I combine the Young Lives dataset with an external dataset detailing environmental shocks experienced – an approach similar to Doyle (2015). However, this paper differs by testing for the direct effects that early life rainfall has, whereas Doyle (2015) uses these measures as instrumental variables. I also further the approach taken by Shah and Steinberg (2015) through the inclusion of labour market outcomes data. This allows me to document the persistent effect that early life shocks have on human capital accumulation and labour market outcomes for young adults. I show that positive rainfall increases human capital investment and that this increased investment, in turn, results in a reduced likelihood of joining the labour force at an earlier age. To the best of my knowledge, these questions have not been considered in the context of Ethiopia. The paper also opens the door for future avenues of research in exploring these questions when Round 5 of Young Lives is collected.

The remainder of the paper is organised as follows. Section 2 outlines the theoretical framework; Section 3 presents the data and some descriptive statistics, while Section 4 presents the results. Section 5 conducts robustness checks and Section 6 concludes.

2 Theoretical Preliminaries

Fundamentally, this is a paper about how human capital accumulation relates to employment outcomes, rather than a paper about shocks. In order to shed light on this question, it is possible to exploit early life shocks – in this case, rainfall – and see whether these have an effect on the former. This section presents a simple generalised model for the probability of employment. The model proposes that, controlling for other background characteristics, human capital accumulated over the life-cycle feeds in to the likelihood of an individual being employed. Given the particularly important role it is thought to play, human capital is then modelled in more detail. In the latter model, parents will take into account the incidence of a positive or negative shock when making investment decisions on a child's human capital investment. Human capital accumulation also depends on the investments made during two separate stages of childhood and whether these investments compensate for or reinforce the direction of a shock depends on how easily substitutable investments between the two periods are.

2.1 Theoretical Framework: Employment Outcomes

As mentioned, I introduce a simple model of employment where employment is a function of human capital accumulation over two periods as well as contemporaneous background variables.

$$p(Employment_2) = v(h_1,\ h_2,\ \boldsymbol{\lambda}_{h2},\ \boldsymbol{\omega}_{i2},\ \boldsymbol{\psi}_{j2}) \tag{1}$$

Where $\boldsymbol{\lambda}_{h2}$ is a vector of household characteristics, $\boldsymbol{\phi}_{i2}$ is a vector of individual characteristics and $\boldsymbol{\psi}_{j2}$ includes regional controls for the region of residence.

Human capital in period 1 (h_1) will be a function of certain inputs, including time allocation to activities, such as work or study ($\boldsymbol{\tau}_1$), as well as a set of individual, household and regional characteristics.

$$h_1 = f(\boldsymbol{\tau}_1,\ \boldsymbol{\lambda}_{h1},\ \boldsymbol{\omega}_{i1},\ \boldsymbol{\psi}_{j1}) \tag{2}$$

In turn, human capital in period 2 (h_2) will be a function of human capital accumulated in period 1, as well as a similar set of contemporaneous inputs.

$$h_2 = g(h_1,\ \boldsymbol{\tau}_2,\ \boldsymbol{\lambda}_{h2},\ \boldsymbol{\omega}_{i2},\ \boldsymbol{\psi}_{j2}) \tag{3}$$

The following subsection presents a more nuanced model of human capital accumulation based on Heckman (2007) that introduces the possibility of shocks experienced in early childhood.

2.2 Theoretical Framework: Human Capital Formation in the Presence of Shocks

A useful theoretical starting point for understanding human capital formation as it relates to shocks is a model of an individual's stock of human capital and its responses to investments over time.[1] Defining h as human capital and modelling it as being linear in investments made in a simple two-period model, Heckman (2007) suggests the use of the constant elasticity of substitution (CES) function due to its adaptability:[2]

$$h = A[\gamma I_1^{\phi} + (1-\gamma)\ I_2^{\phi}]^{1/\phi} \tag{4}$$

For some level of total investment, $I_1 + I_2$, the elasticity of substitution, $1/(1-\phi)$, and the share parameter, γ will both affect h. Using (4) as a basic framework, an exogenous shock to education (as a form of investment in human capital) during the first period of childhood can be introduced. The effect of either a positive or negative shock can be represented as follows:

$$I_1 + \mu_g \tag{5}$$

Substitution into (4) yields equation (6):

$$h = A[\gamma(I_1 + \mu_g)^{\phi} + (1-\gamma)\ I_2^{\phi}]^{1/\phi} \tag{6}$$

Assuming that investments are responsive, a number of studies of the early origins of human capital development and eventual labour market outcomes focus on estimating the changes in human capital as a response to shocks – $\partial h/\partial \mu_g$. The direction of these responses – whether they are compensatory or reinforcing – will depend on the substitutability of investments between periods (which is based on what the parameter ϕ is equal to). To see this, a parent's Cobb-Douglas utility function where the child's human capital formation is traded off against parents' consumption is assumed:

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[1] Almond and Currie (2011a) provide an overview of the theoretical considerations for these types of models that originate in Grossman (1972).

[2] A two period model is considered to keep the model tractable. The CES function also avoids the rather strong assumption of perfect substitutability between investment periods (Almond & Currie, 2011a).

$$U_p = (1 - \alpha)\log(C) + \alpha\log(h) \quad (7)$$

If there is relatively easy substitution between investment in period 1 and investment in period 2 ($\phi > 0$), then it will be optimal for parents to compensate for the shock. Alternatively, in the case of low substitutability ($\phi < 0$) parents should simply reinforce the effect of the shock by reallocating investment. The elasticity of substitution has implications for the estimates of the biological effects – such as nutrition or health – reported in studies. These will tend to be overstated in the case of low substitutability and understated in cases of high substitutability (Almond & Currie, 2011a). Empirically, Ayalew (2005), Dendir (2014) and Doyle (2015) all find evidence of reinforcing investment behaviour in Ethiopia.

2.3 Empirical Framework and Estimation Strategy

Empirical tests of theories of human capital accumulation through allocation of resources between siblings tend to use outcomes such as completed education as a proxy for parental investments.[3] Therefore, in this paper, I adopt the approach of using educational attainment in period 2 to examine human capital investments for the Young Lives Ethiopian older cohort. However, for period 1 I use the Peabody Picture Vocabulary Test (PPVT) score. The benefit of using the PPVT score as opposed to more commonly used measures of education such as enrolment rates and primary school completion rates is that the former measures output, while the latter function as inputs (Woldehanna & Gebremedhin, 2015). The PPVT is a vocabulary test and is intended as an assessment of verbal ability and academic aptitude.

In order to estimate the effects of early life rainfall shocks on employment outcomes in late adolescence, I use a linearised version of the models presented above and estimate comparative statics using the measures of human capital and labour market data from Ethiopia. The simplest empirical model used to do so can be presented as follows:

$$W_{ijt} = \beta_0 + \beta_1\theta_{jt} + \beta_2 h_{it} + \varepsilon_{ijt} \quad (8)$$

The dependent variable in this case – W_{ijt} (called "Any Work") – is a dummy variable coded as 1 if an individual i, in cluster region j, is either employed or mixing study and work and coded as 0 otherwise. With the addition of controls, similar specifications are used to

[3] Griliches (1979), Behrman et al. (1994) and Ashenfelter and Rouse (1998) all provide examples of such work carried out in developed countries.

determine the probability of an individual working only and being self-employed (these outcomes are described further in Section 3). θ_{jt} is a vector of early life rainfall shocks in cluster region j, at time t. Finally, h_{it} is a measure of human capital for individual i at time t. I estimate this model using OLS. For proper identification to be achieved in (9), the zero conditional mean assumption, $E(\varepsilon_{ij}|\theta_j, h_i) = 0$ must hold – where I temporarily drop the time subscript for simplicity and focus on the "Any Work" outcome. This will allow for β_1 and β_2 to be consistently estimated. In particular, the covariance between the explanatory variables and the error term must be equal to zero:

$$E(\theta_j.\ \varepsilon_{ij}) = 0 \tag{9}$$

$$E(h_i.\ \varepsilon_{ij}) = 0 \tag{10}$$

The advent of positive or negative rainfall shocks is quasi-random. Thus, it is likely that condition (9) will hold. However, it is more likely for condition (10) be violated. A violation of (10) would create bias in the estimate on measures of human capital. This possibility will be explored further and discussed in the robustness section. The preceding discussion surrounding consistent and unbiased estimation of the coefficients equally applies to the remainder of the specifications estimated.

To estimate the process of human capital formation thought to underpin labour market outcomes, I once again linearise the models outlined previously. The empirical model estimated – both for PPVT score and education in Round 4 – is written as follows:

$$h_{ijht} = \alpha_0 + \alpha_1\theta_{jt} + \alpha_2\tau_{it} + \delta\lambda_{ht} + \varphi\omega_{it} + \zeta\psi_{jt} + \nu_{ijht} \tag{11}$$

Where θ_{jt} is defined as before, while λ_{ht} is a vector of household characteristics, ω_{it} is a vector of individual controls, τ_{it} is time usage, ψ_{jt} is a vector of regional controls and ν_{ijht} is the error term. Household characteristics include a wealth index,[4] access to electricity, expenditure, the number of children in the household and an urban locality dummy. Individual characteristics include a gender dummy, self-efficacy index,[5] age in months and a dummy for whether a child was stunted during Round 2.

[4] The wealth index ranges from 0-4 and is constructed based on three separate indices that measure housing quality, services quality and a consumer durables ownership index.

[5] The self-efficacy index ranges from 1-2 and has been constructed based on Dercon and Singh (2012).

While similar considerations relating to the consistent estimation of the coefficients as discussed above apply, an additional issue relating to inference arises due to the structure of the data. As implied by the subscript j – which denotes the cluster region – individuals in Young Lives are sampled from within the same cluster sites, which number around 20. This structure presents a potential problem for estimating the standard errors due to the possibility of within-group dependence and the outcomes of individuals within the same cluster being correlated (Cameron, Gelbach, & Miller, 2008).[6] This would therefore hinder proper inference based on the estimates. Thus, I make use of wild bootstrapping as suggested by Cameron et al. (2008) in order to account for the possibility of within-group dependence in a small number of clusters.

2.4 Wild Bootstrap Procedure

In data exhibiting a clustered structure, with the possibility of intra-cluster correlation in outcomes, the usual OLS standard errors will tend to underestimate the true standard errors. Nonetheless, it is possible to correct for the presence of intra-cluster correlation using a generalised form of the White (1980) heteroskedastic-consistent estimate for OLS standard errors. Such a correction allows for heteroskedasticity as well as error correlation within the cluster and is easily implemented in STATA using the cluster option (Cameron et al., 2008).

A problem arises, however, if there are few clusters because the aforementioned cluster-robust standard errors have asymptotic justification and assume that the number of clusters tends to infinity. In particular, with fewer than around 40 clusters, it becomes problematic to estimate consistent standard errors – resulting in difficulties for inference. As such, Cameron et al. (2008) propose the use of wild bootstrapping in order to provide asymptotic refinement. The method involves resampling entire clusters. Broadly, bootstrap methods produce a set of pseudo-samples from the original sample and calculate the statistic of interest for each of these pseudo-samples. The distribution of this statistic across pseudo-samples is then used to deduce that of the original sample statistic (Cameron et al., 2008). The wild bootstrap, in

[6] Indeed, calculations of intra-cluster correlation for the outcomes PPVT score, Years of Education, "Any Work", Working Only and Self Employment reveal that the intra-cluster correlations for these outcomes are 0.343, 0.268, 0.132, 0.066 and 0.135, respectively.

particular, takes into account the group structure of the errors.[7] The procedure also relaxes two strong assumptions made by the residual cluster bootstrap method; namely, that the error vectors are i.i.d. (although the error variance might differ across clusters), and that all the clusters within the dataset are of equal size.[8]

The method is apposite in this case due to the relatively small number of clusters in the Young Lives data – around 20 cluster sites. Moreover, the number of individuals within each cluster varies according to the cluster – meaning that the residual cluster bootstrap method is rendered inappropriate due to the violation of its second assumption. Since the usual clustered standard errors are likely problematic, I use a wild bootstrap throughout this paper, performing $R = 1250$ replications for each.[9] As such, the results presented in Section 4 of this paper report the p-values obtained from the wild bootstrap instead of the usual or clustered standard errors.

3 Data and Descriptive Statistics

3.1 Young Lives: Ethiopian Older Cohort

The Young Lives project is an international longitudinal study focusing on various dimensions of childhood poverty. The study has tracked 12, 000 children since 2002 across 4 different countries. This paper uses data from Rounds 1, 2 and 4 for the Older Child cohort of children in Ethiopia. This sample of 1000 children born in 1994-1995 has been surveyed since they were aged between 7.5 and 8.5 years old in 2002. Round 4 of survey data collection was completed in 2014, when the Older Cohort was aged between 19.5 and 20.5. The choice to exclude Round 3 – when the children were aged between 15.5 and 16.5 – was made in order to avoid sample selection issues where latent unobservables might be driving the decision to remain in education following the completion of primary school. Although there is no minimum school leaving age in Ethiopia, primary school ends when students are around 14 years old. Only students passing a regional exam are allowed to enrol in high

[7] The procedure is also preferable to using an alternative method of dealing with a small number of clusters due to Moulton (1986, 1990) since Moulton correction-type methods also assume errors are i.i.d. rendering them invalid under heteroskedasticity.

[8] For a more detailed discussion of the wild bootstrap method, see Cameron et al. (2008).

[9] Although Cameron et al. (2008) use 1000 replications in the Monte Carlo simulations they conduct, I choose 1250 replications to allow STATA to output more precise p-values that can be rounded to 3-decimal places.

school (Broussar & Tekleselassie, 2012). Thus to avoid potential sample selection biases, I focus on human capital accumulation up to around age 12 by excluding Round 3.

The random sample of households was selected from 20 communities in Addis Ababa, Amhara, Oromia, Southern National, Nationalities and People's Region (SNNPR), and Tigray. Combined, these regions account for 96% of Ethiopia's population of over 94 million. The survey was intentionally designed to over-sample poor and food-poor communities so as to favour children from poor backgrounds in eventual policy decisions and research agendas and is thus intentionally not nationally representative (Wilson, Huttly & Fenn, 2006).[10]

At the individual child level, the Round 4 survey includes information on a variety of personal variables, such as education, health and, importantly, employment. The inclusion of Round 4 of the survey allows for each individual's full educational history until late adolescence to be taken into account. Moreover, the Young Lives data benefits from the rich set of information that has been collected for participants and their surroundings in the survey. Additionally, the data also includes measures of survey participants' ability over various subsequent rounds, such as the PPVT score.

A central concern with longitudinal data is, of course, sample attrition and the resulting biases. Compared to other longitudinal studies, the Young Lives survey has had a low attrition rate: 8.4% in total between Round 1 and Round 4 for the Older Cohort. The majority of this attrition has been due to survey participants moving abroad (Woldehanna & Pankhurst, 2014). Overall, there appears to be insufficient evidence of non-random attrition on observables, which could lead to attrition bias. Moreover, provided the attrition rates are limited, biases attributable to attrition on unobservables should also remain relatively unimportant (Dercon & Outes-Leon, 2008).

[10] Wilson et al. (2006) provide an in-depth discussion of how the sampling was conducted.

3.2 Descriptive Statistics

Table 1: Employment Status by Gender

Employment Status	Female	Male	Total
Unemployed	19 (4.5%)	16 (3.3%)	35 (3.9%)
Employed	97 (23.2%)	181 (37.3%)	278 (30.8%)
Not Economically Active	44 (10.5%)	20 (4.1%)	64 (7.1%)
Mixing Study and Work	96 (22.9%)	153 (31.6%)	249 (27.5%)
Studying Only	163 (38.9%)	115 (23.7%)	278 (30.8%)
Total	419 (100%)	485 (100%)	904 (100%)

Source: Young Lives Ethiopian Older Child Cohort, Round 4 2014. Own Calculations.
Notes: Column percentages in parentheses. Figures have been rounded. Employment is defined as an individual having worked at least once during the preceding week or having a full-time job.

Table 1 presents a summary of the main dependent variable of interest, employment status, and its subcategories. Through the combination of the various subsets of the Young Lives data, a final sample size of 904 out of the 908 individuals in Round 4 is reached. At age 19, 31% of these individuals have left education and are employed, while 31% remain in fulltime education only. Interestingly, the proportion of females only studying is greater than that of the males in the sample. Although the sample is not nationally representative, as discussed above, this finding runs counter to the general tendency for developing countries to exhibit significant gender gaps in access to education as well as in a number of other spheres (Todaro & Smith, 2012). In total, 28% of individuals in the sample are studying and working at the same time, although this proportion varies according to gender.

Table 2 presents the summary statistics for the outcome variables, other variables of interest and for the rainfall shock variables. The nature of the rainfall shock variables is explained further in the following subsection, detailing the source for the rainfall data.

Table 2: Summary Statistics

	Mean	Standard Deviation	N
Any Work	0.583	0.493	904
Working Only	0.308	0.462	904
Self Employed	0.357	0.479	904
Years of Education	8.209	2.757	880
Log of PPVT Score	4.262	0.385	879

Hours of Study (Round 2)[11]	7.128	2.221	904
Hours of Work (Round 2)[12]	4.411	2.384	901
Hours of Study (Round 4)	5.203	4.583	904
Hours of Work (Round 4)	6.119	4.147	904
Rainfall Variables			
Prenatal Annual Rainfall Shock	0.696	0.532	904
Prenatal Belg Rainfall Shock	0.465	0.622	904
Prenatal Meher Rainfall Shock	0.302	0.561	904
Age 0 Rainfall Shock	-0.0708	0.672	904
Age 1 Rainfall Shock	-0.208	0.719	904
Age 2 Rainfall Shock	0.371	0.589	904
Age 3 Rainfall Shock	0.0708	0.538	904
Age 11 Rainfall Shock	0.711	0.453	904
Age 12 Rainfall Shock	0.289	0.453	904
Age 13 Rainfall Shock	0.195	0.593	904

Source: Young Lives Ethiopian Older Child Cohort, Round 4 2014; Round 2 2006. African Flood and Drought Monitor. Own Calculations.
Notes: Values rounded to three decimal places.

The outcome variables of interest are constructed as follows. As mentioned previously, "Any Work" is a dummy variable taking on a value of 1 if an individual is either working only or mixing work and study, and 0 otherwise. Similarly, "Working Only" captures only those individuals who are employed. The "Self Employed" dummy includes all individuals who are working for themselves or within their household – since the Young Lives survey does not distinguish between self-ownership of a business or farm or ownership by another household member. Individuals can be considered self-employed even if they are mixing this type of work with study. "Years of Education" measures the number of years of completed formal education during Round 4.

3.3 African Flood and Drought Monitor (AFDM)

The Young Lives survey includes information on whether households have experienced shocks in the preceding four years. A potential problem with this data, however, is that it is self-reported. As such, there is likely to be measurement error and a degree of subjectivity – particularly with environmental shocks such as droughts or flooding. Moreover, the measure might not fully capture the extent of the drought experienced and due to its subjectivity,

[11] The hours of study variable includes both hours spent at school and hours spent studying outside of school.

[12] Child work hours is made up of hours spent per typical day in the previous week caring for others, performing domestic tasks, working on the family farm and performing paid activities. As in Woldehanna and Gebremedhin (2015), the self-reported hours of engagement is used, since the latter find no significant difference between the child and the caregivers' responses. Importantly, "child work" is considered a broader term than "child labour" (Akabayashi & Psacharopoulos, 1999).

may be endogenous.[13] Therefore, I circumvent this issue by using data from the AFDM database.

Using the AFDM data, I construct a variable for drought exposure for the prenatal period and up to age 3 (inclusive). I create indices for climatic shocks experienced by the communities that the survey respondents inhabit. The AFDM provides monthly data on the Standardised Precipitation Index (SPI), which measures the occurrence of droughts and floods based on the number of standard deviations of precipitation relative to an area's mean. Thus, precipitation below the mean (where the SPI takes on a negative value) indicates a drought, but also captures the severity of the drought. The measure is also useful in capturing positive rainfall shocks – indicated by a positive value for the SPI. Overall, the SPI provides an idea of an area's rainfall history and can be narrowed down to sub-regions across different periods of time (Edwards & McKee, 1997). Similar to Doyle (2015), I match the SPI data at the cluster-level using cluster GPS coordinates and use the 12-month SPI to construct a vector of annual drought exposure. For the prenatal period, I also create an index of drought exposure in the important rainfall seasons – Belg and Meher – using the 3-month SPI. For the purpose of this paper, I define the variables "rainfall shock" as equal to 1 if rainfall measured by the SPI is greater than 0.5 standard deviations above the mean for that area over the relevant time period. The variables are defined as -1 if rainfall is less than 0.5 standard deviations below the mean and 0 otherwise. This allows for a relatively simple interpretation of the results.

Belg runs from February until April, while Meher lasts from June until September. These seasons are crucial for harvesting various crops upon which many Ethiopians' livelihoods depend, with erratic or insufficient rainfall affecting the schedule for planting and growing crops (Carter et al., 2004). Belg in particular is characterised as the short rainy season, with failures, delays or uneven distributions of precipitation during the period usually leading to shortages in staple foods and agricultural households' livelihoods being threatened (Carter et al., 2004). In the following section, I investigate the consequences of the effects of early life

[13] For example, an individual with reduced cognitive ability might not accurately report or recall an environmental shock, but might also be less likely to be employed.

rainfall shocks on test scores. I also test for any long-term effects of these shocks on completed education in late adolescence.

4 Results

4.1 Preliminary Results

This section presents the main results of the paper. First, the results of some preliminary estimations of early life rainfall shocks on the probability of an individual being involved in any sort of work are presented in Table 3. Column (1) includes prenatal rainfall shocks during the critical Belg and Meher seasons, an annual prenatal measure of rainfall, shocks experienced during the critical development period (ages 0-3) and the window of transition to secondary school (ages 11-13) as controls.[14] The Belg and Meher seasons were controlled for during the prenatal period to capture any effects that a rainfall shock during these critical seasons might have on a child when in utero. In addition to the rainfall measures in column (1), columns (2) and (3) include PPVT score and educational attainment at age 19 as controls, respectively. The results in the first three columns indicate that early life rainfall does appear to have statistically significant effects on employment outcomes several years later, with coefficients on prenatal rainfall during Meher ranging from -0.297 to -0.260. Educational attainment is also highly significant, with each additional year of education completed reducing the probability of being involved in any kind of work at around age 19 by 3.8%.

One benefit of the Young Lives data is its collection of children's time-usage information. It is therefore possible to control for the hours of work and hours of study in order to tease out any intensive margin changes in work or school attendance arising from shock exposure. Thus, the possibility of understating the substitution effects between work and school as a result of rainfall shocks − which would otherwise be due to only work or education being observed − is mitigated. In columns (4) and (5), I show that contemporaneous rainfall impacts time allocation at age 12, with current year positive rainfall shocks being associated with 0.921 fewer hours of work and 1.532 more hours of study relative to usual rainfall years.

[14] The exact year of birth is not observed in the data. In order to calculate the shock variables, a year of birth variable was generated to equal survey year minus current age (converted from age in months). As a result, there will inevitably be some noise in these measures. This also applies to the measures indicating a shock during the Belg and Meher seasons.

This implies children work around 1.8 hours more in drought years compared to positive rainfall years and study almost three hours less during drought years. Conversely, positive prenatal rainfall is associated with increased hours of work and reduced hours of study. This is consistent with findings that increased prenatal rainfall has lasting positive health effects (for example, on height) transmitted through nutritional pathways (Dercon & Porter, 2014). As such, children perceived as more robust may be more likely to be involved in domestic activities.

Table 3: Effect of Rainfall Shocks On Probability of Working

	(1) Any Work	(3) Any Work	(2) Any Work	(4) Hours of Work (Round 2)	(5) Hours of Study (Round 2)
Prenatal Annual Rainfall Shock	0.255**	0.218*	0.165	1.800***	-0.722**
	(0.042)	(0.082)	(0.166)	(0.002)	(0.018)
Prenatal Belg Rainfall Shock	-0.173*	-0.135	-0.100	-0.694	0.490
	(0.086)	(0.168)	(0.202)	(0.138)	(0.390)
Prenatal Meher Rainfall Shock	-0.297***	-0.268***	-0.260***	-1.145***	0.559*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.054)
Age 0 Annual Rainfall Shock	-0.194***	-0.200***	-0.153**	-0.734**	0.141
	(0.002)	(0.002)	(0.011)	(0.040)	(0.628)
Age 1 Annual Rainfall Shock	0.072**	0.074**	0.094***	-0.292	0.069
	(0.042)	(0.035)	(0.006)	(0.648)	(0.850)
Age 2 Annual Rainfall Shock	0.069	0.073	0.082	0.263	-0.580
	(0.325)	(0.270)	(0.272)	(0.880)	(0.586)
Age 3 Annual Rainfall Shock	-0.141	-0.142	-0.135	-0.212	0.157
	(0.242)	(0.216)	(0.222)	(0.604)	(0.618)
Age 11 Annual Rainfall Shock	0.002	-0.015	-0.022	-0.332	0.316
	(0.971)	(0.886)	(0.832)	(0.610)	(0.574)
Age 12 Annual Rainfall Shock	-0.009	-0.008	0.054	-0.921***	1.532***
	(0.876)	(0.894)	(0.463)	(0.006)	(0.000)
Age 13 Annual Rainfall Shock	-0.031	-0.038	-0.054		
	(0.548)	(0.443)	(0.317)		
Log of PPVT Score		-0.098*			
		(0.067)			
Years of Education (Round 4)			-0.038***		
			(0.002)		
Constant	0.568***	0.999***	0.907***	4.134***	6.795***
	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	904	879	880	901	904
R^2	0.114	0.121	0.152	0.159	0.145

Source: Young Lives Round 2, Young Lives Round 4, African Flood and Drought Monitor. Own Calculations.
Notes: OLS Estimates. Wild bootstrap p-values are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.010$

This result appears surprising initially, given the findings that school enrolment falls with higher rainfall in rural India, where children face a greater opportunity cost of attending school due to higher agricultural wages resulting from increased agricultural productivity during excess rainfall seasons (Shah & Steinberg, 2015). Nonetheless, the results in Table 3 are broadly consistent with the notion that parents make reinforcing investments in Ethiopia and are thus displaying preferences for efficiency (Dendir, 2014; Doyle, 2015). According to the predictions of the model for human capital formation, this result implies that it is difficult to substitute investments across periods in childhood. The remainder of this section attempts to explore the possible channels through which such effects might be transmitted.

4.2 Human Capital Accumulation

The specifications presented in Table 4A explore the effects of early life rainfall shocks on PPVT in Round 2 and constitute an estimation of (11). These are an attempt to estimate the effect of a shock on human capital, $(\partial h / \partial \mu_g)$. In this case, PPVT score at around age 12 is used as a measure of human capital.

For PPVT scores, only prenatal shocks and shocks experienced at ages 11 and 12 are included as controls in column (1). Interestingly, even when not controlling for hours of work or hours of study, a positive rainfall shock at age 11 is associated with a decrease in PPVT scores. Column (2) includes the full set of background controls, including time use, but excluding any rainfall data. Columns (3) and (4) control for prenatal rainfall shocks and the full set of rainfall shocks, respectively. Column (4) shows that the negative effect of a lagged positive rainfall shock (a shock experienced at age 11) on PPVT is robust to the inclusion of the full set of controls as well as early life rainfall shocks in other periods. It reveals that positive rainfall shocks experienced contemporaneously (at age 12) also adversely affect PPVT score, being associated with a 12.8% drop in the score relative to drought years, all else equal. While the effect of early life shocks on health outcomes, educational attainment and wages has been tested previously, few papers test the possible links between these shocks and human capital accumulation measured by test scores. Exceptions include Shah and Steinberg (2015), Akresh et al. (2010) and Maccini and Yang (2009). Akresh et al. (2010) find negative effects of prenatal shocks in Burkina Faso, while Maccini and Yang (2009) find that human capital among Indonesian adults is positively affected by rainfall during early stages of life. The results in Table 4A are broadly consistent with findings of these papers.

Table 4A: Effect of Rainfall Shocks On PPVT Score

	(1) Log PPVT Score	(2) Log PPVT Score	(3) Log PPVT Score	(4) Log PPVT Score
Hours of Work (Round 2)		-0.010	-0.009	-0.009
		(0.157)	(0.162)	(0.166)

Hours of Study (Round 2)		0.012	0.011	0.010
		(0.110)	(0.203)	(0.238)
Prenatal Annual Rainfall Shock	-0.334***		-0.065	-0.029
	(0.002)		(0.115)	(0.574)
Prenatal Belg Rainfall Shock	0.296***		0.036	0.097*
	(0.000)		(0.366)	(0.066)
Prenatal Meher Rainfall Shock	0.351***		0.115**	0.151***
	(0.000)		(0.040)	(0.000)
Age 0 Annual Rainfall Shock				-0.018
				(0.624)
Age 1 Annual Rainfall Shock				0.069
				(0.179)
Age 2 Annual Rainfall Shock				0.052
				(0.498)
Age 3 Annual Rainfall Shock				-0.002
				(0.936)
Age 11 Annual Rainfall Shock	-0.173*			-0.105*
	(0.053)			(0.059)
Age 12 Annual Rainfall Shock	0.026			-0.064*
	(0.566)			(0.058)
Full Controls	No	Yes	Yes	Yes
Observations	879	853	853	853
R^2	0.219	0.371	0.379	0.393

Source: Young Lives Round 2, African Flood and Drought Monitor. Own Calculations.
Notes: OLS Estimates. Wild Bootstrap p-values are in parentheses. Full controls include regional fixed effects, household characteristics and individual characteristics. * p<0.10, ** p<0.05, *** p<0.010

Table 4B estimates (11) for the second period – using educational attainment in Round 4 as the outcome variable. Column (1) includes the full set of background controls but omits any rainfall shocks. Columns (2) to (4) again progressively include these shocks. Strikingly, even after controlling for time use, rainfall still has positive impacts on educational attainment. This includes the transition period to secondary education, where a positive rainfall shock experienced at age 12 results in around 1.18 additional years of education relative to drought experienced at the same age. PPVT score at age 12 is also predictive of educational attainment, with estimates ranging from 0.527 to 0.600 (indicating that a 1% increase in PPVT score is associated with an additional 0.006 years of education), as is the number of hours of study at age 12.

Overall, column (4) indicates that positive early life rainfall shocks appear to have positive effects on educational attainment – with shocks experienced at age 0 and at age 3 both being associated with an increase in educational attainment. The results indicate that positive rainfall shocks during the window of transition into secondary education are actually associated with increased educational attainment in the case of Ethiopia, countering findings from rural India (Shah & Steinberg, 2015). Thus, Tables 4A and 4B together show that although test scores are lower during and immediately following a high rainfall year, educational attainment is actually positively impacted. These results are broadly consistent with prior literature – where more early life rainfall is associated with greater amounts of education and more human capital accumulation during childhood, as well as consumption (Almond & Currie, 2011b; Maccini & Yang, 2009). Interestingly, rainfall affects these outcomes over and above the roles played by other explanatory variables.

Table 4B: Effect of Rainfall Shocks On Years of Education

	(1) Years of Education	(2) Years of Education	(3) Years of Education	(4) Years of Education
Log PPVT Score (Round 2)	0.539*	0.527**	0.527**	0.600**
	(0.059)	(0.040)	(0.046)	(0.026)
Hours of Study (Round 2)	0.232***	0.235***	0.235***	0.227***
	(0.003)	(0.003)	(0.003)	(0.002)
Hours of Work (Round 2)	-0.030	-0.029	-0.029	-0.025
	(0.544)	(0.536)	(0.539)	(0.562)
Hours of Work (Round 4)	-0.065**	-0.063**	-0.063**	-0.045**
	(0.049)	(0.045)	(0.046)	(0.049)
Hours of Study (Round 4)	0.108***	0.106***	0.106***	0.119***
	(0.000)	(0.000)	(0.000)	(0.000)
Prenatal Annual Rainfall Shock		-0.345	-0.345	-0.180
		(0.269)	(0.269)	(0.645)
Prenatal Belg Rainfall Shock		0.416	0.413	0.070
		(0.106)	(0.232)	(0.840)
Prenatal Meher Rainfall Shock		0.072	0.069	-0.073
		(0.768)	(0.811)	(0.755)
Age 0 Annual Rainfall Shock				0.643***
				(0.003)
Age 1 Annual Rainfall Shock				-0.126
				(0.366)
Age 2 Annual Rainfall Shock				0.112
				(0.606)
Age 3 Annual Rainfall Shock				0.899***
				(0.005)
Age 11 Annual Rainfall Shock			0.007	0.297
			(0.982)	(0.242)
Age 12 Annual Rainfall Shock				0.591**
				(0.021)
Age 13 Annual Rainfall Shock				0.268
				(0.323)
Constant	1.684	1.719	1.712	0.460
	(0.296)	(0.237)	(0.226)	(0.688)
Full Controls	Yes	Yes	Yes	Yes
Observations	793	793	793	793
R^2	0.539	0.543	0.543	0.566

Source: Young Lives Round 2, Young Lives Round 4, African Flood and Drought Monitor. Own Calculations.
Notes: OLS Estimates. Wild Bootstrap p-values are in parentheses. Full controls include regional fixed effects, household characteristics and individual characteristics for both rounds. * p<0.10, ** p<0.05, *** p<0.010

Returning to the model, the results indicate that educational investments made in the face of shocks in Ethiopia reflect a preference for behaviour that reinforces the direction of the shock, as opposed to compensating for it. While a large positive rainfall shock might otherwise lead to reduced educational attainment in India – particularly at the critical age (around 11 to 13 years old) when the transition between primary and secondary school occurs – in Ethiopia this does not appear to be the case. Indeed, it appears as though positive rainfall shocks have a positive effect on education at age 12, seemingly keeping children who are at the margin in school. This is consistent with the aforementioned effects that rainfall shocks have on the hours of work and hours of study at age 12. Given the positive effect that increased hours of study at age 12 has on educational attainment at age 19, this allows for an initial understanding of the transmission mechanisms underlying how rainfall shocks in childhood affect human capital accumulation. A possible interpretation might be that a positive rainfall shock results in better livelihoods and parents can therefore afford to send their children to school. The results therefore seem to suggest that parents are willing to send their children to school when they are able to afford it. Nevertheless, they also raise the question of how shocks affect intra-household allocation of labour – whether other members of the household take up extra work in order for the child to attend school. One possibility is the household hiring assistance in a positive rainfall shock year, since rainfall can act as a shifter of agricultural wages (Shah & Steinberg, 2015). Such questions are beyond the scope of this paper, however, and are therefore not considered further.

In terms of the theoretical model, the results suggest that – at least, amongst poor Ethiopian households – there is low substitutability between consumption and human capital investment, since parents appear to display reinforcing behaviour. This is indicated by the positive coefficients on rainfall shocks at age 11 in Table 4B, column (4). This is consistent with previous evidence suggesting that dropout rates are high in Ethiopia during periods of drought due to, at least in part, the effect droughts have on agricultural households' livelihoods (Rose & Al-Samarrai, 2001; Yamauchi, Yohannes & Quisumbing, 2009). In Ethiopia, unlike rural India, the higher opportunity cost of attending school arising from higher wages resulting from increased productivity during rainfall seasons does not appear to outweigh the preference for human capital accumulation. I now turn to the second question posed in this paper: whether early life rainfall affects eventual labour market outcomes?

4.3 Employment Outcomes

As mentioned, rainfall shocks can be useful in shedding light on the process of human capital formation during childhood and on how this might have consequent impacts on employment later. Exploring the issue is complicated by the variety of situations the Young Lives children find themselves in. While some have left education and entered the labour force by age 19, others are only studying and yet another subsample is mixing study and work. Breaking categories down into their respective sub-samples is problematic for two reasons. Firstly, it would mean that the analysis would suffer from issues of statistical power due to a greatly reduced sample size. Second – and perhaps more worryingly – testing the individual subsamples would raise a number of questions surrounding sample-selection bias. It would seem very implausible that latent unobservables are not to some extent driving decisions made to leave education or to mix education with work. Thus, I attempt to sidestep these issues by creating the aforementioned set of dummy variables to use as dependent variables.

Table 5A presents results of the models run using “Any Work” as the dependent variable. Perhaps unsurprisingly, the number of years of education is significant, with the estimated coefficients ranging from -0.03 to -0.02 across the specifications. These imply that each additional year of educational attainment reduces the likelihood of an individual being involved in work and is likely capturing the effect of individuals who have completed secondary education and have progressed to tertiary education. Column (3) shows that, in this sample, rainfall experienced at ages 11-13 does not have a significant effect on the probability of working. Conversely, the effects of early life rainfall are significant, with the direction of the effect switching at age 1. At age 19, then, more education and human capital accumulation are associated with a decreased likelihood of being part of the labour force. Tentatively, these results also speak to the possibility of dynamic complementarities suggested by Heckman (2007), where greater accumulation in an earlier period leads to increased returns to investment at a later stage. In other words, those children who complete secondary school are more likely to enter tertiary education, but also more likely to be studying only, possibly because remaining in education offers higher returns than entering the labour market. This supports the notion that the labour market places a premium on education and human capital accumulation is seen valuable to some extent.

Table 5A: Employment Outcomes

	(1) Any Work	(2) Any Work	(3) Any Work
Years of Education (Round 4)	-0.030**	-0.028**	-0.020*
	(0.011)	(0.021)	(0.075)
Log PPVT Score (Round 2)	-0.052	-0.029	-0.043
	(0.389)	(0.530)	(0.352)
Prenatal Annual Rainfall Shock		0.164**	0.163*
		(0.042)	(0.083)
Prenatal Belg Rainfall Shock		-0.156**	-0.117
		(0.014)	(0.192)
Prenatal Meher Rainfall Shock		-0.126	-0.215***
		(0.333)	(0.002)
Age 0 Annual Rainfall Shock			-0.248***
			(0.002)
Age 1 Annual Rainfall Shock			0.089***
			(0.000)
Age 2 Annual Rainfall Shock			0.162*
			(0.054)
Age 3 Annual Rainfall Shock			-0.168
			(0.123)
Age 11 Annual Rainfall Shock			-0.082
			(0.286)
Age 12 Annual Rainfall Shock			0.024
			(0.550)
Age 13 Annual Rainfall Shock			-0.012
			(0.854)
Full Controls	Yes	Yes	Yes
Observations	714	714	714
R^2	0.191	0.205	0.245

Source: Young Lives Round 2, Young Lives Round 4, African Flood and Drought Monitor. Own Calculations.
Notes: OLS Estimates. Wild Bootstrap p-values are in parentheses. Full controls include regional fixed effects, household characteristics and individual characteristics for both rounds. * p<0.10, ** p<0.05, *** p<0.010

Much of the significance associated with rainfall shocks during the prenatal period especially – as indicated by the results in Table 3 – is no longer apparent in column (3). This occurrence can potentially be understood through the concept of mediation as outlined by Baron and Kenny (1986). With the addition of various background controls and human capital, the significance of rainfall shocks during the prenatal period is reduced. This points towards some mediation effects and sheds light on the channels through which rainfall shocks might affect employment outcomes – through rainfall's effect on human capital accumulation. In particular, controlling for human capital accumulation as well as the various background controls indicates that rainfall's impact on employment is transmitted through paths of human capital accumulation and rainfall's effect on, for example, stunting. This is consistent with the results from Dercon and Porter (2014) and corroborates evidence found for Ecuador (Rosales, 2014). Alternatively, different types of shocks might shape employment and self-employment differently.

Table 5B reports the results of the "Working Only" and "Self-Employment" dummy variables run on the same set of controls. As columns (1) to (3) show, human capital is again predictive of employment, consistent with the results for the entire sample of working individuals. As before, the effects of rainfall shocks no longer appear to be significant when controlling for additional characteristics in column (3), indicating mediating effects of human capital accumulation.[15] Interestingly, human capital does not have any effects on the likelihood of an individual being self-employed, while early life rainfall (at ages 0-2) exhibits similar effects on the likelihood of self-employment as it does on the likelihood of engaging in any type of work – meaning that the self-employed subsample could be driving the results in Table 5A, column (3).

Table 5B: Working Only and Self-Employment Outcomes

	(1) Working Only	(2) Working Only	(3) Working Only	(4) Self Employment	(5) Self Employment
Years of Education (Round 4)	-0.052***	-0.049***	-0.047***	-0.004	-0.001
	(0.002)	(0.002)	(0.002)	(0.632)	(0.866)
Log PPVT Score (Round 2)	0.012	0.002	0.011	-0.081	-0.088
	(0.794)	(0.928)	(0.842)	(0.261)	(0.304)
Prenatal Annual Rainfall Shock		0.171***	0.175*	0.013	0.013
		(0.000)	(0.089)	(0.910)	(0.840)
Prenatal Belg Rainfall Shock		-0.102**	-0.137	-0.036	-0.021
		(0.026)	(0.107)	(0.654)	(0.869)
Prenatal Meher Rainfall Shock		0.056	-0.005	-0.020	-0.117
		(0.226)	(0.926)	(0.875)	(0.160)
Age 0 Annual Rainfall Shock			-0.054		-0.188***
			(0.187)		(0.002)
Age 1 Annual Rainfall Shock			-0.036		0.122**
			(0.424)		(0.030)
Age 2 Annual Rainfall Shock			-0.081		0.234**
			(0.248)		(0.013)
Age 3 Annual Rainfall Shock			-0.035		-0.102
			(0.408)		(0.182)
Age 11 Annual Rainfall Shock			0.070		-0.071
			(0.219)		(0.285)
Age 12 Annual Rainfall Shock			0.071		0.056
			(0.133)		(0.338)
Age 13 Annual Rainfall Shock			0.010		0.001
			(0.818)		(0.965)
Full Controls	Yes	Yes	Yes	Yes	Yes
Observations	716	716	716	716	716
R^2	0.162	0.185	0.193	0.144	0.176

Source: Young Lives Round 2, Young Lives Round 4, African Flood and Drought Monitor.
Notes: OLS Estimates. Wild Bootstrap p-values are in parentheses. Full controls include regional fixed effects, household characteristics and individual characteristics for both rounds. * p<0.10, ** p<0.05, *** p<0.010

[15] Ancillary OLS regressions analogous to those presented in Table 3 were run, with the dependent variable as the "Working Only" dummy. The results of these indicated significant effects of prenatal rainfall shocks on the probability of being employed only – with positive shocks having a negative effect.

The results indicate that human capital accumulation is predictive of involvement in employment, but not for the subsample of individuals deemed to be self-employed. More interestingly, even after controlling for a wide range of explanatory variables, rainfall shocks continue to exhibit persistent effects. This is particularly the case for prenatal rainfall, as indicated in columns (2) and (3) of Table 5A. Prenatal rainfall also impacts positively on PPVT scores, as a measure of cognitive ability. While rainfall during the transition window into secondary education impacts education, this impact is no longer apparent when looking at employment outcomes. It therefore appears that rainfall's effect during this period is captured by education.

5 Robustness Checks

While rainfall patterns are quasi-random shocks and are most likely exogenous, there may potentially be other aspects of rainfall shocks – whether positive or negative – that could affect the results. This section considers some possible alternative explanations for what might be driving human capital accumulation during rainfall shocks. These alternative explanations would constitute a violation of equation (10). I also consider some heterogeneities in the severity of the shocks experienced, since the effects outlined might display nonlinearities depending on the severity of the shock.

5.1 Health Effects

The amount of rainfall in a given year may increase the incidence of diseases – for example, if there is excess water following a positive rainfall shock, illnesses such as malaria or diarrhoea may be more prevalent. The evidence of clear links between increased prevalence of these illnesses and rainfall is mixed – for example, Bandyopadhyay et al. (2012) find rainfall shortage increases the incidence of diarrhoea, while frequent flooding has been associated with greater prevalence of diarrhoea in Bangladesh, India, Mozambique and the United States (Curreiro et al., 2001). Such a case could confound the results in this paper. It is therefore worth investigating whether health effects might be playing a role in school attendance in Ethiopia. Given the reinforcing behaviour displayed by parents as indicated by the results presented above, such factors might be causing the estimates to be biased downwards – if positive rainfall shocks do indeed result in worse health outcomes. Because data is available on all Young Lives index children's household members, I test for overall health impacts of rainfall shocks on all children in the Young Lives sample as well as their siblings. This has the benefit of increasing the sample size in order to increase statistical power as well as allowing age to be controlled for, since younger children might be more vulnerable to disease or illness.

Using the household roster data from Round 2, I construct the number of days of illness over the previous month due to diarrhoea, cough and fever for each household member between the age of 5 and 17. I then test for overall health impacts of rainfall shocks, as measured by days of illness. I also test for rainfall shocks' effects on total medical expenditures – composed of the amount (in Ethiopian Birr) spent on consultations and treatment and other medical expenses over the last 12 months.

Table 6: Effect of Rainfall Shocks on Health

	(1) Number of Days Ill	(2) Number of Days Ill	(3) Number of Days Ill	(4) Health Expenditure (ln Birr)	(5) Health Expenditure (ln Birr)	(6) Health Expenditure (ln Birr)
Age 11 Annual Rainfall Shock	1.511		1.355	0.215		0.171
	(1.095)		(1.109)	(0.174)		(0.168)
Age 12 Annual Rainfall Shock		1.603	1.332		0.347*	0.314
		(1.235)	(1.266)		(0.193)	(0.187)
Observations	2761	2761	2761	1727	1727	1727
Mean Dependent Variable	3.718	3.718	3.718	4.656	4.656	4.656
R^2	0.005	0.005	0.006	0.156	0.160	0.163

Source: Young Lives Round 2, African Flood and Drought Monitor. Own Calculations.
Notes: OLS estimates. Clustered Standard Errors in parentheses. Controls include age, gender and regional fixed effects. Regression includes only children residing in YL households aged between 5 and 17 (inclusive). * p<0.10, ** p<0.05, *** p<0.010

The results presented in Table 6 indicate that there is no significant effect of rainfall shocks in current or previous years on the number of days spent ill or health expenditures.[16] These results support the notion that children are no more or less healthy in periods of drought as opposed to periods of excess rainfall. While I use wild bootstrap p-values in the main specifications in Section 4, overall the results are quite similar to those obtained using the analytical standard errors. Therefore, in this robustness section I use the clustered analytical standard errors for simplicity.

[16] The F-statistics for the coefficients displayed in column (3) and column (6) are 1.83 and 1.76, respectively and their associated p-values are 0.187 and 0.198.

5.2 Teacher Absenteeism

Another potential challenge for identification is the possibility that children in Ethiopia are attending school less during periods of drought if teacher absenteeism is higher during these periods. Such an effect would bias the reported estimates upwards. If rainfall shocks do indeed act as shifters of wages, then it is equally plausible that the trade-off faced by school children and their families applies to teachers. The Young Lives data does not include explicit information on teacher absenteeism. However, survey respondents are asked to name the three worst aspects of their school. Among the possible responses is teacher absenteeism. Using these responses from Round 2, I identify communities where 15% or more of the children surveyed in that community regard teacher absenteeism as a problem.[17] I construct a dummy variable that takes on a value of 1 for all respondents resident in these communities and 0, otherwise. I then regress this as an outcome on current and previous rainfall shocks and present the results in Table 7.

Table 7: Effect of Rainfall Shocks on Teacher Absenteeism

	Teacher Absent (Round 2)
Age 11 Annual Rainfall Shock	-0.007
	(0.051)
Age 12 Annual Rainfall Shock	-0.208
	(0.139)
Mean Dependent Variable	0.103
Observations	904
R^2	0.307

Source: Young Lives Round 2, African Flood and Drought Monitor. Own Calculations.
Notes: OLS estimates. Clustered Standard Errors in parentheses. Controls include regional effects and an urban area dummy.
* p<0.10, ** p<0.05, *** p<0.010

While likely a very rough measure of the issue, the data do not allow for a more refined approach to be taken. The results indicate that neither a contemporaneous rainfall shock, nor a lagged one appear to have an effect on teacher absenteeism, supporting the notion that absenteeism amongst teachers during rainfall shocks – whether negative or positive – is not driving the results. This observation is consistent with findings that teacher absenteeism rates are relatively low in Ethiopia and that absenteeism rates tend to be lower in rural areas relative to urban areas (Zike & Ayele, 2015). Since children in rural areas are likely to be

[17] This value for the cut-off was selected because it is closest to the 90th percentile value for the percentage of children sampled in a community indicating that teacher absenteeism was a problem. As such, these communities are the most likely to suffer from teacher absenteeism.

more sensitive to rainfall shocks, the relatively low absenteeism rates amongst teachers in these areas supports the result that rainfall shocks do not have a significant impact on teacher absenteeism.[18]

5.3 Heterogeneity in Shock Severity

One issue not fully captured by the rainfall shock variables is the possibility of the outcomes being affected differently based on the severity of the shock experienced. While increased rainfall might be beneficial, excessive precipitation could lead to flooding and therefore have adverse effects. Similarly, a mild drought might not have as dire repercussions as a very severe drought – for instance, the latter might kill off livestock, leaving a household in a poverty-trap it is unable to recover from, impacting human capital accumulation in the process (Carter et al., 2004). I explore these possibilities by defining new treatment dummies according to the severity of a shock experienced.[19] Given the significance of the prenatal and age 0 shocks in the preceding results, I include only these shocks. However, due to the limitations of the data, I am unable to construct indices for moderate or severe droughts (negative shocks) in the prenatal stage and thus focus only on positive shocks.

Table 8 Effect of Early Life Positive Rainfall Shocks by Severity

	(1) Any Work	(2) Working Only	(3) Self Employment	(4) Log PPVT Score	(5) Years of Education (Round 4)
Moderate Prenatal Positive Annual Shock	0.095	-0.039	0.087	-0.087	0.373
	(0.067)	(0.065)	(0.078)	(0.079)	(0.628)
Severe Prenatal Positive Annual Shock	-0.180**	-0.029	-0.118**	0.181***	1.160**
	(0.080)	(0.057)	(0.042)	(0.063)	(0.507)
Moderate Age 0 Positive Annual Shock	-0.443***	-0.218***	-0.290***	-0.319***	0.405
	(0.075)	(0.060)	(0.086)	(0.079)	(0.658)
Severe Age 0 Positive Annual Shock	0.100	0.133	-0.018	0.610***	-0.555
	(0.112)	(0.085)	(0.093)	(0.149)	(0.834)
Observations	855	855	855	879	855
R^2	0.193	0.146	0.147	0.231	0.275

Notes: OLS estimates. Clustered standard errors in parentheses. Columns (1) - (3) control for education and PPVT score. Column (5) controls for PPVT score. All columns include gender and regional fixed effects controls. * p<0.10, ** p<0.05, *** p<0.010

[18] For a detailed discussion on teacher absenteeism in Ethiopia, see Zike and Ayele (2015).

[19] A moderate shock treatment dummy takes on a value of 1 if the absolute value of rainfall measured by the SPI is greater than 1 standard deviation above the mean for that area over the relevant time period, and 0 otherwise. Similarly, a severe shock is defined as being in excess of an absolute value of 1.5 for the SPI measure. These definitions are also used in the construction of both the positive rainfall shock and drought treatment dummies.

The results presented in Table 8 nonetheless accord with discussion in Section 4. As evidenced by the estimates on “severe positive rainfall shocks” in columns (4) and (5), larger positive rainfall shocks positively impact human capital accumulation. Nonetheless, the changing sign between the moderate and severe shock estimates points to the existence of non-linear effects. More over, in column (4), the absolute value of the significant coefficients almost doubles when comparing across shock severity. For example, a moderate shock at age 0 has a coefficient of -0.319, while the coefficient on the severe shock is 0.610. This indicates that not all positive rainfall shocks are the same. Ideally, a larger dataset with more variation and multiple cohorts would allow for a more complete range of shock severity to be controlled for.

5.4 Other Concerns

One concern of investigating the effect of early life rainfall on cognitive development in this case is that only children who have survived until the age of 8 are included in the sample.[20] Thus, if early childhood drought exposure impacts childhood mortality, children who survive are positively selected and are more likely to have greater health endowments and possibly cognitive outcomes to begin with as a result. This selection issue would bias the estimated effects downwards, since the true effect of a drought is in a sense being overcome to some extent by the natural endowments of the survivors. Therefore, the results presented here should be interpreted with caution and could be used as upper bounds of the estimated effects.

This study can be potentially broadened in scope with the availability of new data. The evidence indicates that rainfall shocks do have significant effects even with a relatively limited sample size, pointing towards the possibility for a similar study with expanded scope to be conducted. The sample in this paper is limited to one cohort of Young Lives. Thus, in some years no single community might have been exposed to a particular type of rainfall shock. As a result, this paper cannot fully explore all questions related to these phenomena due to the nature of the data.

[20] As mentioned, Round 1 for the Ethiopian Older Child cohort conducted when the children were around 8 years old.

6 Conclusion

In this paper, I have estimated the effect of childhood human capital accumulation on employment outcomes using a unique panel dataset from Ethiopia. In order to shed light on the processes underlying human capital formation, I use rainfall data matched at the cluster-level for the prenatal period and the critical windows of development (ages 0-3) and transition between primary and secondary school (ages 11 to 13). To my knowledge, no other papers explicitly test the relationship between employment and lifetime exposure to rainfall shocks. I outline a simple model of employment probability and incorporate a model of human capital investment in the presence of shocks. Using OLS estimation and the quasi-random nature of rainfall patterns, I find evidence of positive rainfall shocks increasing long run educational attainment. I also find that the likelihood of employment is reduced with each additional year of education – indicating that higher accumulation in earlier periods feeds into higher accumulation in later periods and therefore a decreased likelihood of leaving education to join the labour force. These results suggest that, in Ethiopia, investments in human capital tend to reinforce the direction of shocks experienced during critical childhood development periods and that, tentatively, children's education is seen as valuable, at least by caregivers.

The implication of the results for the model's predictions is that – in this context – substitution between human capital investments across periods is relatively inelastic. I find additional evidence indicating that one of the mechanisms driving these decisions might relate to the distribution of labour and time allocation within household, given a rainfall shock. To account for the small number of clusters and intra-cluster correlation, I use a wild bootstrap and find that the results are nonetheless significant. Finally, I test some alternative explanations such as the possibility that health effects or teacher absenteeism rates affected by rainfall are in turn driving the results and find that these explanations do not appear to play a role in determining the primary results. Thus, it appears that in years when rainfall is high, poor Ethiopian households can afford to keep children in school. It should also be noted that the sample used here includes urban households. These are less likely to be as sensitive to rainfall shocks. Therefore, the effects here might be understated to some extent and should be interpreted with caution.

The results speak to the broader policy issues facing the Ethiopian government and support the introduction of programmes such as conditional cash transfers. It appears that providing households with a buffer to withstand the potentially adverse effects of droughts will allow for greater amounts of human capital accumulation to occur. This is important given that the labour market seems to place a premium upon greater human capital accumulation, since it appears that individuals with larger amounts of human capital are willing to remain in education for longer. If poor countries are to improve their stock of human capital, policies must be carefully designed to ensure that the accumulation process is robust to external shocks. Overall, understanding what might lead to better youth employment outcomes in future is likely an important step in breaking the cycle of poverty – thus reducing future child poverty.

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