The origins of cognitive skills and non-cognitive skills: the long-term effect of in-utero rainfall shocks in India[†]

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Abstract

Skills are an important predictor of labour, education, and wellbeing outcomes. Understanding the origins of skills formation is important for reducing future inequalities. This paper analyses the effect of shocks in-utero on human capital outcomes in childhood and adolescence in India. Combining historical rainfall data and longitudinal data from Young Lives, we estimate the effect of rainfall shocks in-utero on cognitive and non-cognitive skills development over the first 15 years of life. We find negative effects of rainfall shocks on receptive vocabulary at age 5, and on mathematics and non-cognitive skills at age 15. The negative effects on cognitive skills are driven by boys, while the effect for both cognitive and non-cognitive skills are driven by children of parents with lower education, suggesting that prenatal shocks might exacerbate pre-existing inequalities. Our findings support the implementation of policies aiming at reducing inequalities at very early stages in life.

Keywords: skills formation, in-utero, rainfall shocks, India

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1. Introduction

The foetal origins hypothesis (FOH) advocated by David J. Barker proposes that the in-utero period is an important and critical period where adverse (or favourable) conditions can have persistent and long-term effects on adult health (Barker, 1990; 1998). Since then, growing economic literature finds that shocks that occur during the in-utero period can affect various future outcomes such as adult health, human capital, and earnings (Almond and Currie, 2011). Research in epidemiology and developmental neuroscience suggests that the prenatal period is crucial in influencing the brain structure and neural development which subsequently affect cognitive function (Rooij et al., 2010; Andersen, 2003; Thompson and Nelson, 2001). However, little is known about the importance of this period for the formation of personality and non-cognitive skills. Understanding the early formation of non-cognitive skills is of particular interest given the impacts of these skills on key economic outcomes later in life, such as employment and earnings (Heckman et al., 2006; Cunha and Heckman, 2008; Cunha et al., 2010), academic achievement, and social competence (Borghans et al., 2008; Almlund et al., 2011).

This paper analyses the effect of shocks that occur in-utero on both cognitive and non-cognitive skills development over childhood and adolescence. The exposure to weather shocks among pregnant mothers can affect their children human capital development through three potential mechanisms. First, weather shocks can generate a disproportionate amount of stress and interfering directly on brain development in a very critical period (*biological channel*). Second, weather shocks might affect crops production and the related changes in prices and income consequently would affect the consumption of food and other health inputs (Hoddinott, 2006; Skoufias and Vinha, 2013) (*nutrition channel*). Finally, the (net) impact of the shock will depend on the compensating mechanisms intervening in mitigating the detrimental effect of the shock with potential distributional effects.

This paper exploits rainfall fluctuations to test: (i) whether exposure to environmental shocks during pregnancy negatively affects cognitive and non-cognitive skills development throughout childhood and adolescence; (ii) whether the effects vary depending on the intensity of the shock and (iii) the number of shocks suffered during the gestation period; (iv) whether the impacts of being exposed to shocks differ across pregnancy trimesters, and (v) whether the in-utero shocks have a distributional effect by gender and socio-economic status.

Our identification of the causal effect of rainfall variation on cognitive and non-cognitive skills development relies on the assumption that, conditional on community-by-month fixed-effects, temporary rainfall deviations from historical averages are uncorrelated with other latent determinants of skills development during gestation and through childhood and adolescence.

Our analysis uses the Young Lives (YL) data, a longitudinal dataset of children born between January 2001 and June 2002 in Andhra Pradesh (nowadays including the states of Andhra Pradesh and Telangana) and followed for five rounds of data collection over 15 years. We combined the YL dataset with monthly frequency gridded information on precipitation from the University of Delaware to construct a community-by-month weather dataset that spans between 1900 and 2014. Andhra Pradesh is vulnerable to several climate shocks including cyclones, storm surges, floods, and droughts. According to the Revenue Disaster Management of Government of Andhra Pradesh and UNICEF, multiple incidences of heavy rain and flooding has been registered between April 2000 and September 2001, corresponding to the gestational period for the YL children. Also, there were reports of drought in the first six months of 2000 in the southern districts of Andhra Pradesh.[4]

Our study contributes to the literature on the effect of shocks in-utero on long-term human capital development in several ways. First, this is one of the few papers in the economic literature investigating the effect of weather shocks happening during the gestation period. Second, we investigate the effect on both cognitive and non-cognitive skills, where evidence on the latter is particularly scarce. Third, we add to the thin body of evidence on how effects evolve over time, throughout childhood to adolescence. Finally, we contribute to the growing literature on the long-term effects of more frequent aggregate shocks, which are far less extreme compared to catastrophic shocks (such as famine episodes and earthquakes) but affect larger populations and are likely to keep occurring in the future.

We find that children who are exposed to rainfall shocks in-utero have lower cognitive skills at age 5 and age 15. More specifically, we find that being exposed to a rainfall shocks in-utero reduces the receptive vocabulary test score (as measured by the Peabody Picture Vocabulary Test - PPVT) at age 5 (in 0.15 points or 5% lower score than the control group including children not affected by any shock in-utero) and the math test score (in 13.6 points

[4] For more information see: https://reliefweb.int/report/india/india-floods-appeal-no-192000-final-report; https://reliefweb.int/report/india/unicef-report-drought-and-floods-india-28-sep-2000

or 2% lower score respect to the control group) at age 15. Additionally, rainfall shocks in-utero reduces children’s core-self-evaluation (CSE), a composite measure of self-esteem, self-efficacy, and locus of control at age 15 by 0.16 points. No statistically significant effects were found between ages 8 and 12. We also document heterogeneity in our findings. The negative impact on children's cognitive scores were driven by boys, but there are no gender differences for non-cognitive scores. Additionally, children of lower educated parents are affected by the shock more than children of parents who had at least completed primary education. Finally, according to our results, being exposed to shocks after the first trimester of pregnancy has the largest detrimental effects on children’s numeracy at age 15 and not differential effect on PPVT scores and CSE scores.

The remainder of the paper is organized as follows. Section 2 briefly reviews the existing literature on the effect of in-utero shocks on human capital development and the potential transmission channels. Section 3 describes the two sets of data used in this paper and the main definitions of the outcome variables of interest, how the gestational period and rainfall shocks are defined. Section 4 shows some descriptive evidence emerging from the data. Section 5 describes the empirical approach and Sections 6 and 7 present and discuss the results and their validity. Section 8 concludes with a summary and discussion.

2. Literature review

2.1 The effect of in-utero shocks on human capital development and later outcomes

Economists have sought to establish the link between prenatal conditions and human capital outcomes frequently exploiting natural experiment to demonstrate causal pathways. Natural experiments either in the form of climate shocks (Maccini and Yang, 2009; Kumar et al., 2014; Andalon et al., 2016), pandemics (Almond, 2006; Banerjee et al., 2010; Fletcher, 2018), famine (Neelsen and Stratmann, 2012), and genocide (Bundervoet and Fransen, 2018) offer a suitable solution to the omitted variables bias concern. One of the first economics study investigating the FOH was conducted by Almond (2006) who studied the long-term effects of in-utero exposure to the 1918 influenza pandemic in the US. He found that cohorts who were in-utero during the pandemic displayed reduced educational attainment, increased rates of physical disability, lower income, lower socioeconomic status, and higher transfer payments compared with other birth cohorts. Similarly, Bundervoet and Fransen (2018) found that children who were in-utero during the genocide in Rwanda were approximately 8% less likely to complete primary school and completed 0.3 years of education less than children who were born a couple of months later.

While the early literature using natural experiments tend to focus on disasters or more extreme shocks, there has been growing economic literature investigating the effect of in-utero exposure to more frequent aggregate events on future outcomes. For example, Almond et al. (2015) and Almond and Mazumder (2011) find that Muslim students exposed to Ramadan in the first half of pregnancy have respectively significantly lower math test scores (between 0.06 and 0.08 standard deviations lower) and are 20% more likely to be disabled as adults, the effect being larger for mental (or learning) disabilities. Similarly, Majid (2015) showed that children in Indonesia exposed to Ramadan in-utero scored 7.8% lower on cognitive tests and 5.9% lower on maths scores.

Similar evidence emerges from studies investigating the effect of weather fluctuations during the gestation period on children's health. Rocha and Soares (2015) find that rainfall shocks during pregnancy can lead to higher infant mortality, lower birthweight and shorter gestation periods in Brazil. Andalon et al. (2016) find that in Colombia, in-utero exposure to moderate low-temperature shocks during the first and second trimester of pregnancy reduces children's length at birth while exposure to moderate heat waves in the third trimester reduces the child's birthweight. In India, Kumar et al. (2014) find that children who experienced drought in-utero have poorer health, measured by weight-for-age z-scores. Similarly, Ahmed and Ray (2017), using YL data, find that children exposed to multiple shocks in-utero have lower weight-for-age and height-for-age z-scores. Notably, the latter paper measures shocks using self-reported information, which may suffer from inaccuracies and recall bias. Our paper overcomes this problem by using direct measures of rainfall data, which accurately measure weather shocks experienced by the household.

There is a growing number of studies analysing the effects of weather shocks on educational outcomes, mainly measured by educational attainment and enrolment and a few on earning outcomes. Maccini and Yang (2009) find that higher rainfall in-utero raises adult women's schooling and socio-economic status in rural Indonesia, but not for men. Thai and Falaris (2014) find that negative rainfall shocks in-utero delays Vietnamese children's school entry and grade progression, between the ages 6 and 19. In India, studies using data from ASER of primary school children, find that children exposed to drought in-utero are less likely to enrol in school, more likely to repeat a grade, and perform worse than their peers in mathematics and reading tests (Shah and Steinberg, 2017).

2.2 The effect of in-utero shocks on personality and non-cognitive skills development

In contrast to the effects on cognitive skills, the literature on the effects of in-utero shocks on non-cognitive skills is almost inexistent. We are aware of only one study by Krutikova and Lilleor (2015) that examines the effect of prenatal exposure to rainfall fluctuations on non-cognitive skills in adulthood in Tanzania, measured using a composite measure of self-esteem, self-efficacy, and locus of control called core self-evaluation. The authors find that exposure to a 10% increase in rainfall deviation from the long-run average in-utero increases an individual's core self-evaluation by 0.08 standard deviations relative to their siblings.[5]

2.3 Biological, nutritional, and behavioural transmission channels

In this section we discuss three transmission channels that might explain the impact of pre-natal shock on human capital development. While we cannot distinguish which of these mechanisms may be in play, we refer to prior literature which may help us theorise the posited mechanisms. One is through an impact on human brain development (*biological channel*) and second is an impact on yields, consumption, and early-life nutrition (*nutritional channel*). Furthermore, we recognize the presence of potential compensating behaviours that might be triggered by initial shocks (likely mitigating the impact) and potential distributional effect at play depending on the household wealth and the gender of the child.

Extensive research in the neuroscience literature has argued that there are different and potentially critical stages of brain development, which can have persistent long-term effects on human behaviour.[6] According to Stiles and Jernigan (2010), human brain development begins in the first trimester of pregnancy. From the third to eighth gestational week (first trimester), rudimentary structures of the brain and central nervous system are established to form the first well-defined neural structure.[7] The period between the eighth gestational week extending to approximately mid-gestation is a crucial period in the development of the neocortex and extends until mid-gestation. The neocortex is important in higher functions such as sensory

[5] Notably, the authors defined the in-utero shock variable using yearly rainfall data. This approach does not allow to control for seasonality as rainfall deviations are computed on yearly basis.
[6] Knudsen (2004) argues that there are two important periods for the brain and behaviour: 'sensitive' and 'critical' periods. 'Sensitive' periods are limited periods during brain development where the effect of experiences on the brain are unusually strong, while 'critical' periods are experiences that occur during the sensitive period but result in irreversible changes to the brain function.
[7] Gestational week refers to the number of weeks post conception (from the mother's last menstrual cycle).

perception, spatial reasoning, conscious thought, and language. In the last trimester of pregnancy, myelination (fatty insulation of neurons) and synaptogenesis (forming of synapses between neurons in the nervous system) begin. According to Thompson and Nelson (2001), all these processes in the prenatal period are essential to the functional architecture of the brain.

Furthermore, maternal conditions such as stress during the pre-natal period can play an important role in foetal programming. Psychiatric studies such as Austin et al. (2005) found that there is an association between self-reports of maternal trait anxiety, perceived stress, and depression, and more problematic infant temperament. More recent research by Aizer et al. (2017) measured stress through the stress hormone cortisol level. The authors show that in-utero exposure to elevated levels of the stress hormone cortisol has detrimental effects on children's educational achievement, cognition, and health.

On the nutritional channels, unexpected variation in rainfall can be argued to affect early-life conditions through a negative impact on yields and consumption. This is particularly relevant in developing countries where a large share of agriculture may be rain-fed and families live out of what they produce, and where mitigation mechanisms are limited. The effect on crops yields varies depending on the farmers' choices in selecting types of crops and productivity-enhancing inputs and their ability to anticipate weather fluctuations (Amare et al. 2018; Bhavani et al. 2017; Dillon et al., 2015; Palanisami et al., 2015). In the short-term, the effect on consumption largely depends on the capacity of the household to respond to the shock by smoothing consumption and using savings. Based on existing literature (Hoddinott, 2006; Datar et al. 2013; Rosales Rueda 2018; Skoufias and Vinha 2012; Skoufias and Vinha, 2013), we expect greater susceptibility of lower socio-economic status households to adverse rainfall shocks due to their more limited capacity to smooth consumption and compensate for shocks. Therefore, weather shocks might have a distributional effect and exacerbate existing inequalities magnifying risks of low-birthweight and malnutrition for children born from poorest families that could have long-lasting consequences (Rosales, 2014).

The negative impact of the shock on yields and consumption might affect early-life nutrition with potential long-lasting consequences. Many studies in medical sciences and psychology suggest that low birth weight and early malnutrition may lead to impaired cognitive development (Linnet et al., 2006; Mara, 2003; Shenkin et al., 2004). Thompson and Nelson (2001) argue that in prenatal months, the developing brain is vulnerable to external insults including malnutrition (but also viral infection, alcohol exposure). Rooij et al. (2010) find evidence to this link; exposure to malnutrition in the foetal period during the Dutch Famine, particularly during the first part of pregnancy, negatively affects selective attention and inhibitory control later in the child's life. Increasingly, the economic literature attempts to quantify the relationship between health outcomes and subsequent cognitive achievement (Lo Bue, 2019; Bharadwaj et al., 2018; Sánchez, 2017; Spears, 2012; Miguel and Kremer, 2004; Glewwe et al., 2001).

The effect of weather shocks on human capital development might also differ by the child's sex. A growing body of evidence suggest that female foetuses are more resilient and adaptive to stress than are male foetuses (DiPietro and Voegtline, 2015; Rosenfeld, 2015). For instance, Walsh et al. (2019) find that maternal stress, both physical and psychological distress, increased the probability of pre-term birth, poorer foetal neurodevelopment (measured by foetal heart rate-movement coupling), and posed a greater risk to male foetuses. On the other side, the economic literature has highlighted higher elasticity of human capital investments in face of rainfall shocks for girls as compared to boys in India (Chatterjee and Merfeld, 2020; Rose, 1999). Thus, the unbalanced intra-household allocation of resources in favour of boys might lead to a more detrimental effect of the shock on girls than on boys.

3. Data

This section first, describes the two main source of data used for the empirical analysis (i.e., the YL data and the rainfall data); second, it defines the main variables used for this analysis.

3.1 Young Lives

The YL survey is a unique longitudinal cohort study following two cohorts of children in Andhra Pradesh and Telangana. For this study, we use the younger cohort data for which we have information since the first years of life. The younger cohort includes circa 2,000 children was born in 2001-2002 when the children were aged between 6 and 18 months.[8] The first study wave was followed by four subsequent rounds in 2006 (age 5), 2009 (age 8), 2013 (age 12) and 2016 (age 15). The attrition rate between rounds 1 and 5 is 6%, which is relatively low compared to other longitudinal studies.

[8] The older cohort consists of circa 1,000 children that were born in 1994-1995 and tracked since about age 8.

The study sites were selected in 2001 using a semi-purposive sampling strategy to oversample poor households. Hence, YL is not a nationally representative survey.[9] The old state of Andhra Pradesh, now comprising both Andhra Pradesh and Telangana state, was divided into 23 administrative districts, each sub-divided into a number of mandals (also called *sentinel sites* or *clusters*), depending on the size of the district. In total, there were 1,125 mandals with generally between 20 and 40 communities (or villages) in a mandal. The sampling design consisted of two stages. In the first stage, 20 mandals were chosen based on a set of economic, human development and infrastructure indicators (Young Lives, 2017). In the second stage, approximately 100 households with a child born in 2001-02 were randomly selected from each mandal. The final sample is spread across 7 districts and 3 regions (Srikakulam and West Godavari in Coastal Andhra; Anantapur and Kadapa in Rayalaseema; Karimnagar and Mahbubnagar in Telangana; and Hyderabad), 20 clusters and 100 communities, including both rural and urban communities.

In all rounds, two main questionnaires were administered to capture various measurements of child development and other household-level characteristics: a child questionnaire with data on child health and anthropometrics (from age 1),[10] cognitive achievements and more specifically receptive vocabulary and numeracy (from age 5 and 8 respectively), non-cognitive skills or personality traits (from age 8) and other individual characteristics; a household questionnaire (from age 1) including data on caregiver background, livelihood, demographic characteristic of household members, socio-economic status, and self-reported shocks. Finally, and most importantly for this paper, YL collects GPS coordinates for all the communities where the YL children live. This information allows us to estimate with precision the YL children's exposure to weather shocks, which will be further explained in Section 3.2.

Cognitive and non-cognitive skills measures

There are two main cognitive indicators used in this analysis: receptive vocabulary and numeracy skills. Receptive vocabulary is measured using an adapted version of the Peabody Picture Vocabulary Test, a widely used test, administered between the ages of 5 and 15 years

[9] Nevertheless, it is shown that the YL sample covers the diversity of children in poor households in Andhra Pradesh (Kumra, 2008).

[10] Considering that only 42.9% of the full sample had their birth weight recorded, we did not use this variable in the analysis. The sample of children whose birth weight is reported is quite selected: children whose birth weights are recorded are socio-economically better off; their mothers have higher education; they live in urban areas; and have fewer siblings.

old (Dunn and Dunn, 1997). Numeracy skills are assessed using mathematics tests developed by YL for the purposes of the survey. The mathematic tests were not designed to be grade-appropriate but incorporate questions at widely differing levels of difficulty: at the basic level, the tests included questions assessing basic number identification and quantity discrimination; at the intermediate level, questions on calculation and measurement; and at the advanced level, questions related to problem-solving embedded in hypothetical contexts that simulate real-life situations (e.g., tables in newspapers). The cognitive tests were collected for all children, regardless of whether they were attending school or not. This feature of the data avoids the selection problem which commonly arises when using school-based data.[11]

The PPVT and the math tests are constructed using Item Response Theory (IRT) models that are commonly used in international assessments such as PISA and TIMSS. The main advantage of IRT models consists of acknowledging item difficulty and enhancing comparability over time and across ages (Leon and Singh, 2017).

For non-cognitive skills, YL collects self-reported information about generalised self-esteem, self-efficacy, and agency measured at age 12 and 15. Self-esteem refers to an individuals' judgement of their own self-value or self-worth and it was measured using the Rosenberg self-esteem scale (Rosenberg, 1965). It has been found to be correlated to conscientiousness and inversely related to the personality trait of neuroticism (Meier et al., 2011). Self-efficacy is measured through the General self-efficacy scale (Jerusalem and Schwarzer, 1992) and it refers to the individual's belief in the own's capabilities to produce given attainments and to cope with adversity (Schwarzer and Jerusalem, 1995; Bandura, 1993). Finally, agency is closely linked to self-efficacy and builds on the concept of locus of control by Rotter (1966). In this case, the objective is to measure a child's sense of agency or mastery over his/her own life. For each non-cognitive measure, children were asked to indicate their degree of agreement or disagreement with five statements measured on a Likert scale. The full list of statements and corresponding distribution and raw score reported in the Annex.[12]

In psychology, self-esteem, self-efficacy, locus of control, and neuroticism measure a latent personality trait known as "core self-evaluations" (CSE), first examined by Judge et al. (1997). Individuals with high CSE think positively of themselves and are confident about their

[11] A validation of the psychometric properties of the PPVT and math scores can be found in Cueto and Leon (2012) and Cueto et al. (2009).
[12] The internal consistency of these scales is documented and discussed in Yorke and Ogando Portela (2018) and Dercon and Krishnan (2009).

own abilities. Conversely, people with low CSE have a negative appraisal of themselves and lack confidence. CSE has been found to be positively correlated with job performance (Judge et al., 1998), the ability to work in a team (Mount et al., 1995), income level and academic achievement (Judge and Hurst, 2007). Judge et al. (2003) developed a core self-evaluation scale including 12 items alike the ones administered in YL.[13] Validation tests show that the measures of self-esteem, self-efficacy, and agency administered in YL have a high degree of correlation. A principal component analysis confirms that items from all three scales load to the first factor which has an eigenvalue of 3.62 and explains 85% of the total variation. The CSE scale constructed has high internal reliability, with a Cronbach's alpha of 0.81. This is supported by the psychology literature that questions the independence of these three related concepts and is cautious about investigating them in isolation (Judge et al., 2002; Block 1995). Thus, we use the first factor emerging from the principal component analysis as a measure of the latent CSE personality traits. The score is standardised within the sample.

3.2 Rainfall data

Rainfall data is obtained from the University of Delaware, possibly the most commonly use climate dataset in the literature (e.g. used in Shah & Steinberg (2017), Rocha & Soares (2015), and Thai & Falaris (2014)). It provides gridded climate data on monthly rainfall precipitations between 1900 and 2014 (Matsuura and Willmott, 2015).[14] This long series of data points are used to compute the monthly historical mean in each of the 100 YL communities in India. To do so, we match the grid points for which rainfall data was available to the GPS locations of the YL communities. For each YL community, the survey collected GPS coordinates using as a reference point the centre of the community either identified as the centre of the main square or, in absence of it, of another point of interests (e.g., city hall, school, post office, church). The distance from each community GPS location to all grid points was calculated and the four grid points closest to each YL community were considered. A distance weight w_g was generated for each grid point g, as follows:

[13] The full list of items in reported in the Annex, in Table A1.

[14] The data can be accessed at the following links at the University of Delaware's website: Terrestrial Air Temperature: 1900-2014 Gridded Monthly Time Series (1900 - 2014) (V 4.01 added 5/1/15) and Terrestrial Precipitation: 1900-2014 Gridded Monthly Time Series (1900 - 2014) (V 4.01 added 5/1/15). Each of the values is a local point estimate at a 0.5-degree of longitude-latitude resolution.

$$w_g = \frac{dist_g^{-1}}{\sum_{g=1}^{4} dist_g^{-1}}$$

with w_g ranging from 0 to 1, with grid points closer to the community having larger weights. The distance weights for the four grid points in each community summed to 1. For each YL community, the monthly rainfall precipitation was calculated as a distance-weighted average of the monthly rainfall registered at the four closest grid points to that community.

To identify shocks and their severity, we compute the month-community Standardized Precipitation Index (SPI), following Lloyd-Hughes and Saunders (2002) methodology. The SPI was first proposed by McKee et al. (1993) to monitor the severity of droughts in Colorado, USA.[15] The primary advantage of using the SPI is simplicity, since the rainfall data is the only information needed (i.e., no information about altitude or soil characteristics are needed). Also, while precipitation is typically not normally distributed, the SPI normalises the data, making wetter and drier climates equally represented. Lloyd-Hughes and Saunders (2002) define rainfall shocks as rainfall fluctuations of at least 1.5 standard deviations away from the historical monthly-and-community specific rainfall mean.

Notably, YL collects self-reported data about shocks, information collected in the first round.[16] The survey questions refer to any shock that occurred since the mother was pregnant, therefore including both the in-utero period and the first year of life (YL children are on average 11.5 months old in round 1). Despite of that, and the broader definition of shock used in the self-reported survey module which does not encompass droughts or floods specifically, we found a substantial correspondence between what the YL households report and the occurrence of shocks as defined using the rainfall data. More specifically, we found an overlap between clusters with a high prevalence of households reporting having been affected by a shock and those hit by strong rainfall fluctuations during the same period as per the rainfall data. This strongly suggests that the rainfall shocks registered in the climate data were indeed perceived and affected the population living in the geographical area where the shock occurred. However, reliance on external data, as opposed to self-reported data on shocks, is preferable, as it addresses concerns of systematic reporting bias besides increasing the precision of estimates (Cameron and Shah, 2013).

[15] SPI is also used by the Indian Meteorological Department for monitoring purposes (http://www.imdpune.gov.in/hydrology/hydrg_index.html).

[16] In 2001/2002 the household head is asked to report any "big changes or events" that decreased the economic welfare of the household since the mother was pregnant with the YL child.

3.3 Defining the in-utero period and rainfall shocks

The YL children were born between January 2001 and June 2002. The date of conception and the gestation period of each YL child is defined using information about the date of birth and assuming 38 weeks (266 days) as an approximation of a normal-term pregnancy, as per the World Health Organization definition.[17] Therefore, the gestational period for YL children is between April 2000 and September 2001. The defined gestation period accounts for premature births. Information about premature births and the number of weeks the child was premature are available in the first survey round as reported by the mother.[18] About 9% of mothers (164 observations) reported that their child was between 1 to 9 weeks premature, with an average of 2 weeks of prematurity. The trimesters of pregnancy were then defined as the periods between week 0 – 12 (first trimester); week 13—27 (second trimester); and week 28 until birth (third trimester).

To identify the community of residence of the mother while she was pregnant with the YL child, we use round 1 information on the community of residence and information about how long the mother has been living in the same community. In the attempt to exclude mothers who may have migrated to the round 1 community of residence to give birth or after the birth of the child, we exclude from the sample mothers who reported to have moved to the community while pregnant or after giving birth, about 6.6% of the sample. Thus, the final sample includes mothers who lived in the community for at least 2 years and up to 40 years before the first round of data collection, with an average of 9.7 years.[19]

Information related to the conception date and place of residence were matched with the relevant rainfall data for the specific community, month, and year. Therefore, for each child, we defined nine variables, one for each month *m* of the gestation period, capturing the monthly rainfall deviations $RD_{i,c}^{y,m}$ for the child *i*, whose mother was living in the community *c* during the years *y* (either 2000 or 2001). $RD_{i,c}^{y,m}$ is the difference between the monthly rainfall in the community of residence and the historical monthly rainfall in the same community:

[17] The World Health Organization define as preterm as giving birth before 37 weeks of pregnancy is completed. See the WHO website: https://www.who.int/news-room/fact-sheets/detail/preterm-birth. Also, most of the papers use 266 days or 38/40 weeks as threshold to define pre-term pregnancies.
[18] There are only 12 cases where the number of weeks the child was premature is not reported. These observations were deleted from the sample.
[19] We cannot exclude that some of the mothers might have spent part of the pregnancy in a different community as the survey question asks "how long have you lived in this community for?", which does not account for temporary short-term migration.

$$RD_{i,c}^{y,m} = R_c^{y,m} - HR_c^m$$

More specifically, $R_c^{y,m}$ is the rainfall in month *m* and year *y* in the community of residence *c* and HR_c^m is the historical rainfall for month *m* in the same community *c*. The historical monthly rainfall is the average monthly rainfall registered in each community during the period 1900-2014. For instance, the historical average rainfall for January in a specific community would be computed by averaging out the monthly rainfall registered in the same community during all the 115 Januaries during the 1900-2014 period.

Following Lloyd-Hughes and Saunders (2002), we defined as a shock any monthly rainfall deviation of at least 1.5 standard deviations above (*positive shock* or *floods*) or below (*negative shock* or *droughts*) the historical monthly average for the same community.[20] To characterize the intensity of the shock we distinguish between *mild shocks* (between 1.5-2 standard deviation above the historical monthly average) and *strong shocks* (any shocks of at least 2 standard deviations above the historical monthly average). It is worth noticing that computing month- and community-specific rainfall deviation accounts for seasonality, besides identifying communities that are historically more prone than others to floods and/or droughts.

There is no consensus in the literature on how long the historical rainfall series (HR_c^m) should be to identify abnormal monthly rainfall. The length of the historical period varies significantly in the literature, with averages calculated from as little as 10 years of data (Krutikova and Lilleør, 2015; Adhvaryu et al., 2018, to the entire range available, often over 100 years with gridded terrestrial datasets (Dinkelman, 2017; Webb, 2019; Carrillo, 2020; Yamashita and Trinh, 2020; Baez et al., 2017 in Mozambique; Andalon et al., 2016 in Colombia). In studies of India, the choice seems arbitrary and no explanation is provided in none of the paper reviewed (Shah and Steinberg, 2017, Kumar et al., 2014). Reasonably, the choice of the time span used to represent 'normal' rainfall is specific to the sample used and should take into account for: first, the potential climate change that might have affected the region over time and; second, potential poor weather station coverage in early periods or large changes in stations densities that might lead to artefacts affecting the trends.

In relation to climate change, we argue that in case of the state of Andhra Pradesh and Telangana there is not a clear increasing or decreasing pattern in the average yearly rainfall during the long historical period suggestive of climate changes significantly affecting rainfall

[20] This terminology is used without any specific reference to the intensity of the rainfall deviation.

and seasonality (see Figure A1 in the Annex). In support to our argument, Krishnan et al. (2020) report that the annual rainfall series over Indian landmass shows a decreasing trend, but those trends are not statistically significant and are irrelevant in the two states studies in our paper.[21]

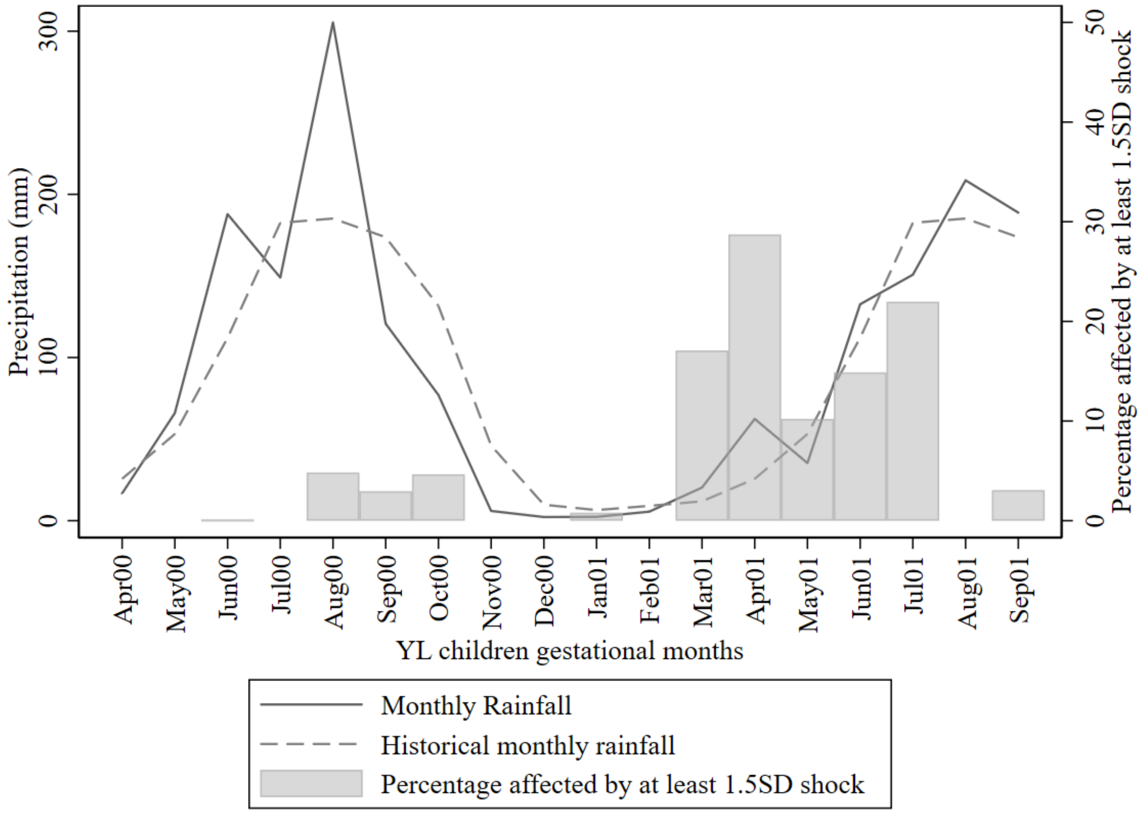
In relation to the weather stations coverage, while there is a clear worldwide increase in weather station coverage in the first half of the 19th century, the same is follow by a similarly clear decrease afterwards.[22] Furthermore, station coverage varies significantly across countries and even within the same country. Unfortunately, the weather data used in this paper do not contain information about the number of stations contributing to each grid point. The Meteorological Department of India-IMD (Minister of Earth Science) uses the historical period 1900-2020 to define abnormalities in rainfall (and temperatures). As there are no clear steering and no evidence suggesting the best historical period to identify abnormal monthly rainfall, we decide avoiding any arbitrary cut point and use monthly rainfall data for the entire 1900-2014 period. Nevertheless, we did some robustness checks that are further discussed in the Results section.

4 Rainfall shocks in India during the YL children in-utero period

According to the Indian Meteorological Department, the climate of Andhra Pradesh is generally hot and humid. The summer extends from March to June where moisture level is quite high, the monsoon rainy season is between June and September (with the pre-monsoon season between March and May and the post monsoon season between October and December) and the winter is between October and February (Guhathakurta et al., 2020). Figure 1 displays the average monthly-and-community specific historical rainfall registered across the 100 YL communities and the average monthly-and-community specific rainfall from April 2000 up until September 2001, corresponding to the in-utero period of the YL children. The average rainfall is reported in millimetres and measured on the left y-axis. The bars show the percentage of YL children affected by a shock of at least 1.5SD during each in-utero month, as reported on the right y-axis.

[21] Decreasing trends in annual rainfall over the period 1901–2015 interests the regions of Kerala, Western Ghats and some parts of central India, including Uttar Pradesh, Madhya Pradesh, and Chhattisgarh as well as some parts of the North-eastern states.
[22] The University of Delaware published a figure depicting the number of (worldwide) weather stations across the whole period (1900-2014), http://climate.geog.udel.edu/~climate/html_pages/Global2017/PrecipStatNum.pdf).

Figure 1: Average monthly rainfall, historical mean and proportion of children hit by a rainfall shock during the in-utero period



Note: The monthly rainfall reported in the figure (solid line) is computed averaging the monthly rainfall across the Young Lives communities for the period April 2000-September 2001. The historical monthly rainfall (dashed line) is the average monthly rainfall registered in each community during the period 1900-2014. Rainfall is measured in millimetres and reported on the left y-axis. The bars represent the proportion of children exposed to a shock (of at least 1.5SD) in each month (right y-axis).

The historical rainfall fluctuations reflect the annual seasonal trend described above, with the wettest months between June and September, and the driest months between December and February. Furthermore, when comparing rainfall fluctuations during the in-utero period against the historical rainfall we observe that most of the shocks occurred during summer and the monsoon season in both years but with particularly intense precipitations happening between March and July 2001. This is likely due to the cyclone that hit Andhra Pradesh in the monsoon season in 2000 (De et al., 2005) and extensive flooding reported in the same areas during the summer 2001 (Ahmed et al., 2013).

The YL communities are distributed across three agro-climatic regions: 42 communities are in Coastal Andhra, 33 in Telangana and 25 in Rayalaseema. 77% of the children were in rural areas in Round 1, and 23% in urban areas. Three out of four YL children have been exposed to an abnormal amount of precipitation (for at least a month) during the gestation period (Table *1*).[23] Furthermore, almost a third of the children (31%) have been exposed to extreme rainfall shocks during the gestation period (2SD or more). The majority of the children who were affected by a shock experienced positive shock (41% experienced only a positive shock, 12% experienced only a negative shock, and 23% experienced both a positive and a negative shock).

Table 1. Prevalence of rainfall shocks of different intensity and nature during pregnancy

Levels of exposure to rainfall shock	**%**	**Obs.**
Affected by a rainfall shock of at least 1.5SD	75.8	1,313
Affected by strong rainfall shock (2SD and above)	30.9	535
Affected by mild rainfall shock (between 1.5SD and 2SD)	44.9	778
None	24.2	419
Type of shock (of at least 1.5SD)		
Negative shock only	12.0	209
Positive shock only	40.8	706
Both negative and positive shocks	23.0	398
Affected by a rainfall shock of at least 1.5SD	75.8	1,313
First trimester	37.0	641
Second trimester	35.9	621
Third trimester	31.5	546
None	24.2	419
Observations		1,732

Note: The sample includes all children tracked since round 1 and across the 5 rounds. The sample is constrained to children whose background characteristics are observed, and at least one of their skills score (PPVT, mathematics or CSE) is measured in all rounds. Percentage affected by the rainfall shock in-utero by trimester can overlap since the in-utero shocks can occur in more than one trimester, depending on the date of conception.

Looking at the geographical distribution of the rainfall shocks during the in-utero period, we find that the prevalence of rainfall shocks (flood and droughts) during the in-utero period is highest in Telangana communities, while Coastal Andhra and Rayalaseema

[23] Nearly half of our sample (45%) only experienced the shock for one month only during the gestation period, 17% experienced for 2 months, 12% for 3+ months.

communities are more prone to positive shocks compared to the communities in the other two regions.

In terms of timing, there are some variations in the incidence of shocks throughout the pregnancy trimesters, but they are roughly equally spread, with a slightly higher prevalence of rainfall shocks during the first and second trimesters.

Table *2* reports some basic characteristics comparing children exposed to a rainfall shock during the gestational period to their peers. All variables are time-invariant except for the rural/urban location of residence measured in round 1. By construction, the place of residence refers to the place where the child was conceived and lived (at least) his/her first year of life. The p-values for a t-test for differences in means between the two groups are reported in the last column. Overall, we find that the exposure to in-utero shocks is homogeneously distributed across the selected subgroups. While the majority of the YL sample live in rural areas (77%), we find that children in urban areas are more likely to have been exposed to shocks in-utero. Although these differences may suggest that children from more advantaged backgrounds are more likely to be affected by shocks, it is reassuring to find that parental education levels are similar across both groups.

Table 2: Comparing children affected and not affected by in-utero shocks

	Exposed to in-utero shock		**No shocks**		**t-test**
	Mean	SD	Mean	SD	p-value
Child characteristics					
Female	0.47	0.01	0.45	0.02	0.554
Male	0.53	0.01	0.55	0.02	0.554
Child's age in months (2016, Round 5)	179.96	0.10	180.12	0.19	0.468
Castes					
Scheduled Caste	0.18	0.01	0.19	0.02	0.633
Scheduled Tribe	0.14	0.01	0.20	0.02	0.004
Backward Caste	0.47	0.01	0.44	0.02	0.341
Other Caste	0.21	0.01	0.17	0.02	0.059
Round 1 location (2002)					
Rural	0.74	0.01	0.87	0.02	0.000
Urban	0.26	0.01	0.13	0.02	0.000
Parent characteristics					
Mother's education					
Incomplete primary or less	0.71	0.01	0.74	0.02	0.252
Completed primary or completed secondary	0.27	0.01	0.24	0.02	0.202
Tertiary education and above	0.02	0.00	0.02	0.01	0.757
Father's education					
Incomplete primary or less	0.56	0.01	0.60	0.02	0.150
Completed primary or completed secondary	0.38	0.01	0.35	0.02	0.254
Tertiary education and above	0.06	0.01	0.05	0.01	0.502
	1,313		419		

Note: The sample is constrained to children whose background characteristics are observed, and at least one of their skills score (PPVT, mathematics or CSE) is measured in all rounds. Being exposed to rainfall shocks is defined as being exposed to a rainfall fluctuation of at least 1.5 standard deviations away from the monthly-community specific historical mean for at least one month during the gestation period. There is no statistically significant difference in prevalence of premature births between children who were exposed to the shock in-utero compared to children who were not exposed (9% and 10% respectively). Parental education is defined as follows: no education up to grade 6 are "incomplete primary or less", grade 7 to 12 as "completed primary or secondary education", and above grade 12 are categorised as "tertiary education and above". Scheduled Castes (SCs) and Scheduled Tribes (STs) are traditionally disadvantaged communities. SCs are the lowest in the traditional caste structure (formerly known as the 'untouchables' and now call themselves Dalit). At the other end of the spectrum, the Backward Classes (BCs) and the 'Other Castes', the latest also called 'Upper Castes' and comprise mostly of 'forward castes' who traditionally enjoy a more privileged socioeconomic status. The p-values for a t-test for differences in means between control group and the treated groups are reported in the third column.

5 Empirical approach

We exploit variations in rainfall across geographic areas (community), months and years of birth to identify the causal effect of shock in-utero on cognitive and non-cognitive skills development. As mentioned, the YL children were born in 100 different communities and although the sampling design was done to identify children of approximately the same age in round 1. The date of births are spread across 18 months, between January 2001 and June 2002 as described above.

We test five main hypotheses. First, exposure to rainfall shocks during the gestational period has long-term effects on cognitive and non-cognitive skills development throughout childhood and adolescence. Second, the effect of in-utero exposure to rainfall shocks increases with the intensity of the shock. Third, whether the effect of the shock increases monotonically with the number of shocks that occurred during the gestation period. Four, the effect of the in-utero exposure to rainfall shock is time-sensitive, i.e. it depends on which trimester of pregnancy the shock occurred. Five, in-utero shocks have a distributional effect by gender and socio-economic status.

The effect of in-utero rainfall shocks on children's future outcomes is specified as follows:

$$Y_{ijc,t} = \propto + \beta_0 S_{ijc} + \gamma C_j + \omega_c + yob_i + mob_i + \varepsilon_{ij,t} \tag{1}$$

where $Y_{ijc,t}$ is the outcome of interest of child *i*, at age *t*, born in the household *j* and whose mother was living in community *c* during pregnancy. The outcomes measured are PPVT scores at ages 5, 8, 12, and 15; mathematics scores at ages 8, 12, and 15; and CSE scores at ages 12 and 15. S_{ijc} is the shock variable and it takes a value equal to 1 if for at least one month during the gestation period the community where the mother of the child was living was exposed to a rainfall shock of at least 1.5 standard deviations, as calculated by the SPI. The main parameter of interest is β_0 which captures the impact of in-utero shocks on the child's outcome. As long as the rainfall shock is exogenous, that is $E(S_{ijc},\ \varepsilon_{ij,t}) = 0$, β_0 is unbiased and provides the causal effect of a rainfall shock on $Y_{ijc,t}$. This will be discussed further at the end of this section.

The vector *C* includes the child's age in months, gender, and his/her caste. This specification also includes maternal community of residence fixed-effects ω_c that are intended to control for any unobservable (time-invariant) community-specific characteristics, that might make some communities more prone to weather shocks or more disadvantaged than others in term of health and education inputs (such as the availability and quality of health services, prenatal care, and education services). The ideal geographical level to be used for the fixed-effect is the community, given that the rainfall variable is defined at the community level.[24] Finally, we include a year of birth fixed-effect, yob_i, and month of birth fixed-effect, mob_i, to account for time trends and potential cofounding effects of being born in a certain month, as discussed below. $\varepsilon_{ij,t}$ is an idiosyncratic error term. In the regressions, standard errors are clustered at the community level.

To capture the heterogeneity of the effect of shocks in-utero we investigate how it varies depending on: first, its intensity (i.e., whether the rainfall shock is of at least 1.5 standard deviations or 2+ standard deviations); second, its duration or frequency (i.e., the number of monthly shocks occurred in-utero); and third, its timing (i.e., during which pregnancy trimester the first shock occurs).

In equation (2), I^k corresponds to three k levels of intensity of the rainfall shock (0 = no shock, the base category; 1 = mild shock; 2 = strong shock). Thus, the parameters of interest, σ_1 and σ_2, correspond to the effect of being exposed to a mild shock and a strong shock, respectively, compared to children who did not experience any shocks in utero.

$$Y_{ijc,t} = \propto + \sum_{k=0}^{2} \sigma_k I_{ijc}^{k} + \gamma C_j + \omega_c + yob_i + mob_i + \varepsilon_{ij,t} \tag{2}$$

In equation (3), we examine whether the effect of the shock is monotonic according to the duration or frequency of shocks in-utero. We include an indicator variable D^l where l represents different categories of shocks durations 0 = no shock, the base category; and the number of shocks that happened during the in-utero period which are categorised as 1, 2, and 3 or more, since 45% of the sample experienced one shock only, 17% experienced 2 shocks and 2% experienced 3 or more shocks.

$$Y_{ijc,t} = \propto + \sum_{l=0}^{3} \pi_k D_{ijc}^{l} + \gamma C_j + \omega_c + yob_i + mob_i + \varepsilon_{ij,t} \tag{3}$$

In equation (4), we explore whether there are key periods during pregnancy when exposure to rainfall shocks are more likely to affect the child's skills development. Given that in our sample some children have been affected by shocks in more than one trimester, we analyse the effect of the shock timing by identifying the effect of the trimester (first, second or

[24] The relatively small sample size might raise concerns about the limited within-community variation with the fixed-effect capturing most of the variation in the data. However, results are similar when fixed-effect at YL cluster level are considered.

third) when a shock first occurred. To do so, we include the variables S^r for whether the shock happened in trimester one, two or three or never happened (base category). We also control for the total number of monthly shocks that occurred throughout pregnancy, indicated by T_{ijc}.

$$Y_{ijc,t} = \propto + \sum_{r=0}^{4} \varphi_r S_{ijc}^r + \delta T_{ijc} + \gamma C_j + \omega_c + yob_i + mob_i + \varepsilon_{ij,t} \quad (4)$$

Finally, we investigate the distributional effect of an in-utero shock by the child's gender and the household socio-economic status. To do so, we estimate equation (1) separately for boys and girls and distinguishing households where the highest educational level completed by the parents corresponds to having completed (or not) primary education.

To identify the effects of in-utero rainfall shocks on children's skills, we rely on the assumption that rainfall shocks are random, which seems to be the case, as shown in

Table *2*. Furthermore, an underlined assumption is that the decision to get pregnant is not timed according to seasonality. As reported in Figure A*2* in the Annex, the date of births are spread across 18 months, between January 2001 and June 2002 and tend to be slightly more common during the monsoon season.[25] The inclusion of month-of-birth fixed effect would control for potential cofounding effect. Furthermore, if mothers did time their pregnancies, then we would find differences in the background characteristics of mothers who gave birth in the monsoon period compared to those who gave birth in a different period, which would invalidate our assumption that rainfall shocks and pregnancy are orthogonal. Table A2 in the Appendix reports the average background characteristics of mothers of children born in the monsoon compared to those not born in the monsoon period. It is reassuring to find that the characteristics of the mothers (education; health, proxied by height; and, location and the number of children) in the two subgroups are largely similar, the only exception being mother's age, but the difference is small by about half a year. A final concern would be if mothers were able to time the pregnancy anticipating weather shocks. However, it seems quite unlikely, as it would require sophisticated forecasts models.

6 Results

Table *3* shows the average effects of experiencing a rainfall shock at any point during the in-utero period on children's cognitive and non-cognitive skills. Like previous studies (Almond et al., 2015; Almond and Mazumder, 2011), we find that being exposed to a rainfall shock reduces children's cognitive skills. In particular, we find that being exposed to a rainfall shock in-utero reduces PPVT scores at age 5 (in 0.15 points or 5% lower score respect to the control group) and the math scores (in 13.6 points or 2% lower score respect to the control group) at age 15. Additionally, we find novel evidence that rainfall shocks in-utero reduces children's non-cognitive skills at age 15 by 0.16 points. These results are robust to alternative definition of the historical period length used to compute a "normal" monthly rainfall.[26]

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[25] Notably, the gestation period for virtually all children in the sample overlap with the monsoon season for at least a month. Only 2 children (0.11% of the sample) were not exposed to the monsoon period at any month during the in-utero period.

[26] Guttman (1999) recommends using a period of at least 50-year to compute SPI values, for computational accuracy. We perform some robustness check using an historical period between 115- and 50 years. Overall, our results seem robust when using different data spans of 50 years+, though less precise as reported in

Besides PPVT, the effects of an in-utero shock seem to only manifest at later ages. While we cannot empirically prove it and fully explain why this occurs, Almond and Currie (2011) argue that there may be "latent disadvantages" which are unobserved, i.e. events in-utero can alter the infant in a way that leads to later disease even in infants who are apparently healthy at birth. The most recent study by Conti et al. (2020) suggests that events occurring in the prenatal period can influence postnatal development without affecting early measured human capital (in most of the cases measured by birth weight). Similarly, we argue that the stronger effects on skills observed at age 15 may reflect the existence of "latent disadvantages" that manifest (or are measurable) only at older ages. Latent disadvantage might not affect the child's ability to compute basic arithmetic at young ages, but possibly more complex and higher abilities measured during adolescence.

Table 3: The effect of in-utero rainfall shocks on children's skills at age 5, 8, 12, and 15

	PPVT IRT	Math IRT	CSE
Age 5	-0.154**		
	(0.072)		
Age 8	-0.047	0.798	
	(0.074)	(5.935)	
Age 12	-0.075	-3.492	0.080
	(0.089)	(5.611)	(0.074)
Age 15	-0.126	-13.652**	-0.161**
	(0.119)	(6.125)	(0.079)
Observations	1313	1697	1315

Note: All specifications control for child's age, gender, and caste, year-of-birth fixed-effects, month-of-birth fixed effects, and community fixed-effects. Standard errors are clustered at the community level. The sample is constrained to children of whom their skills scores are observed at all ages. P-values to show if the estimate is statistically significant from zero is indicated by *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

The negative impact on children's PPVT at age 5 and mathematics at age 15 are driven by boys (see

Table A3 in the Annex for an historical period of 50 years of monthly rainfall data.

Table A*4* in the Annex). Boys who experienced a 1.5 standard deviation shock in-utero had 0.3 standard deviations lower PPVT, significant at the 5% level, whereas the effect on girls are close to zero. Boys who experienced a shock had lower mathematics scores at age 15, significant at the 5% level. Girls experienced lower mathematics scores too, but the effect is not statistically significant. Finally, we did not find any gender differential effects on non-cognitive scores.

Furthermore, we find evidence that in-utero shocks affect both cognitive and non-cognitive skills of children of lower educated parents relatively more than children whose parent have at least completed primary education (see

Table A5 in the Annex). The effect of a shock reduces mathematics and CSE scores at age 15, significant at the 5% level for lower educated parents. Hence, weather shocks might have a distributional effect exacerbating pre-existing inequalities.

We then investigate the effect of being exposed to a rainfall shock during the pre-natal period varies according to the intensity of the shock. More specifically, Table 4 shows the effect of a mild shock and of a strong shock compared to children who have not been exposed to a shock in-utero. As reported in Table 1, strong shocks (2SD or more) are relatively less common that mild shocks as (31% compared to 43% of the sampled have been exposed respectively to strong and mild rainfall shocks during the gestation period). According to our results, both mild and strong shocks have an equally negative effects on PPVT at age 5 and mathematics scores at age 15, the two estimated parameters being not statistically different to one another (Table 4). Furthermore, the negative impacts on PPVT and CSE scores at age 15 seem to be driven by milder shocks, as stronger shocks do not have an impact on those skills at the same age.

Table 4: The effect of in-utero rainfall shocks by intensity, on children's skills at age 5, 8, 12, and 15

		PPVT IRT	Math IRT	CSE
Age 5	≥1.5SD and <2SD	-0.142*		
		(0.081)		
	2SD and above	-0.176**		
		(0.087)		
F-test, mild = strong shock		0.144		
Age 8	≥1.5SD and <2SD	-0.056	-0.861	
		(0.092)	(6.686)	
	2SD and above	-0.031	3.205	
		(0.096)	(6.661)	
F-test, mild = strong shock		0.041	0.416	
Age 12	≥1.5SD and <2SD	-0.134	-6.835	0.018
		(0.085)	(6.042)	(0.092)
	2SD and above	0.029	1.369	0.172
		(0.128)	(7.292)	(0.106)
F-test, mild = strong shock		2.303	1.290	1.470
Age 15	≥1.5SD and <2SD	-0.220*	-13.455*	-0.179**
		(0.132)	(7.198)	(0.087)
	2SD and above	0.041	-13.938*	-0.134
		(0.138)	(7.131)	(0.100)
F-test, mild = strong shock		4.158**	0.004	0.210
Observations		1313	1697	1315

Note: All specifications control for child's age in the specified round, gender, and caste, year-of-birth fixed-effects, month-of-birth fixed-effects, and community fixed-effects. Standard errors are clustered at the community level. The sample is constrained to children of whom their skills scores are observed in every age. The F-test reports the F-statistic when testing the joint significance that the coefficient for mild shocks (≥1.5SD and <2SD) is equal to strong shocks (2SD and above). P-values to show if the estimate is statistically significant from zero (including the p-values for the F-test) is indicated by *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Similarly, as for the intensity of the shocks, we find little evidence of a non-monotonic relationship between the effect of pre-natal shocks on skills development. According to our results, being exposed to one, two, or three or more shocks does not have a differential impact on skills (see

Table A*6* in the Annex).

Overall, these estimates suggest that being exposed to in-utero shocks, but not the intensity or the frequency of the shock, affects children’s future skills development. Arguably, the sample size of the YL children may be relatively small which lack power identifying variation in these effects by shock intensity and frequency.[27]

Finally, we investigate whether the timing of the shock matter. More specifically, we explore whether the impacts of being exposed to rainfall shocks differ depending on whether the child was exposed for the first time to a rainfall shock in the first, second or third pregnancy trimester.

[27] While not shown here, note that in Table 1, most of the shocks were positive or both positive and negative shocks. We find that our estimates are largely driven by positive shocks, given the higher prevalence. The estimated parameters for positive and negative shocks are not statistically significant from one another (results not reported, available on request).

Table 5 shows that in-utero rainfall shocks during the second or third trimester negatively affect the math score at age 15, while no significant effect is found for shocks occurring in the first trimester. Nevertheless, the joint F-test shows that the coefficient estimates are statistically indistinguishable from one another. We do not find any differences in the effect of the shocks by trimester on PPVT scores nor CSE scores.

Table 5: Effect of shocks in-utero on skills development, by trimester in which the first in-utero rainfall shock occurred

		PPVT IRT	Math IRT	CSE
Age 5	1st trimester	-0.133		
		(0.131)		
	2nd trimester	-0.151		
		(0.124)		
	3rd trimester	-0.147		
		(0.125)		
F-test, trim 1= trim 2= trim 3		0.045		
Age 8	1st trimester	-0.149	11.174	
		(0.140)	(9.404)	
	2nd trimester	-0.131	11.570	
		(0.124)	(9.095)	
	3rd trimester	-0.094	3.234	
		(0.132)	(9.404)	
F-test, trim 1= trim 2= trim 3		0.145	0.835	
Age 12	1st trimester	-0.133	-12.705	0.032
		(0.146)	(11.441)	(0.148)
	2nd trimester	-0.060	-10.879	-0.042
		(0.132)	(8.720)	(0.129)
	3rd trimester	-0.199	-13.741	-0.016
		(0.126)	(9.540)	(0.119)
F-test, trim 1= trim 2= trim 3		0.965	0.063	0.332
Age 15	1st trimester	-0.273	-17.812	-0.125
		(0.199)	(12.150)	(0.152)
	2nd trimester	-0.032	-17.576*	-0.087
		(0.185)	(9.767)	(0.143)
	3rd trimester	-0.209	-22.571**	-0.086
		(0.167)	(9.891)	(0.127)
F-test, trim 1= trim 2= trim 3		1.751	0.270	0.138
Observations		1313	1697	1315

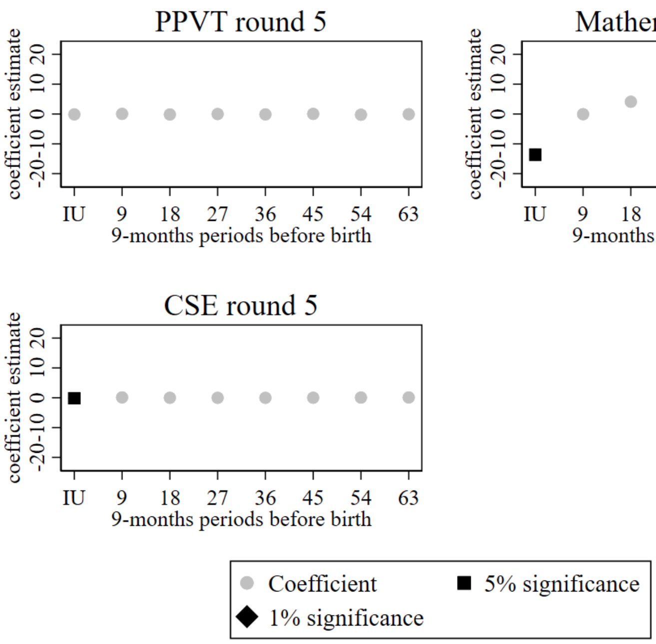
Note: 1st trimester is the gestation period between week 0—12, 2nd trimester is week 13 – 27, 3rd trimester is between week 28 – birth. All specifications control for child's age in the specified round, gender, and caste, total number of shocks that occurred in-utero, year-of-birth fixed-effects, month-of-birth fixed effects, and community fixed-effects. Standard errors are clustered at the community level. The sample is constrained to children of whom their skills scores are observed in every age. The F-test reports the F-statistic when testing the joint significance that the coefficient for each of the trimesters are equal. P-values to show if the estimate is statistically significant from zero (including the p-values for the F-test) is indicated by *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

7 Falsification Tests

One concern is that the negative effects of in-utero exposure to rainfall shocks on skills development may be confounded with omitted variables. To verify that this is not the case, we estimate the effects of shocks (of at least 1.5SD) occurring in each 9-months period before the child's conception date up to 7 years (or 63 months), on children's mathematics, PPVT, and CSE scores at age 15.

In Figure 2, each marker corresponds to the estimated parameter capturing the effect of the shock happening in each 9-months periods in-utero (i.e., coefficients reported in Table 3) and before conception on the child's skills score. If the results presented in the previous section were spurious and driven by omitted variables, the results in Figure 2 and those in the previous section should be similar. Overall, there is no such evidence.[28] Figure 2 shows evidence of no significant effects of rainfall shocks on PPVT, Maths, and CSE scores before conception. This suggests that the effect of rainfall on children skills development is only relevant during the in-utero period and that there are no other mechanisms (e.g., maternal nutrition) through which previous rainfall shocks might affect children's skills development.

Figure 2: Estimates on exposure 0 to 7 years before birth on PPVT, Mathematics and CSE scores at age 15



Note: IU refers to the 9-months in-utero period. Figure plots the estimated coefficients on any rainfall shock occurred in the 9-months period in-utero and pre-conception (up to 7 years) on children' skills at round 5. The estimated coefficients correspond to separated specifications on each of the three scores at age 15 for each 9-monthsperiod before birth, with the same controls specified in the baseline regression in Table 3, and clustered at the community level. The squares represent p-value at the 5% significance level, and the diamonds represent p-values at the 1% significance level.

[28] Results from a multiple hypothesis testing confirm these results. We calculated the Westfall-Young stepdown adjusted p-values, which control for the probability of making any Type I error (i.e., a false positive). Results are available upon request.

8 Discussion

Differences in education, labour, and social outcomes later in life can be originated at very early stages. In this paper, we analyse the importance of in-utero conditions for the formation and development of cognitive and non-cognitive skills in a sample of children and teenagers in India. More specifically we exploit variations in rainfall across geographic areas (community), months, and years of birth to identify the causal effect of shock in-utero on cognitive and non-cognitive skills development throughout childhood and adolescence. Our results indicate that being exposed to rainfall shocks when in-utero are detrimental to children's receptive vocabulary at age 5, and on mathematics and non-cognitive skills at age 15. The effect for cognitive skills is driven by boys, while the effect for both cognitive and non-cognitive skills are driven by children of parents with lower education, suggesting that prenatal shocks might exacerbate pre-existing inequalities.

The most important limitation of this study is the inability to investigate the mechanisms through which the unveiled effects arise. As discussed in the paper the effects of rainfall shocks on child's development can be explained by changes in crops production, prices, and income with an impact on consumption and nutrition or by a disproportionate amount of stress caused to the mother and interfering directly on brain development in very critical period. Finally, the (net) impact of the shock will depend on the compensating mechanisms intervening in mitigating the detrimental effect of the shock with potential distributional effects. Our results suggest that, regardless of any investment strategy the household might put in place, being exposed to a weather shock during the in-utero period has a negative long-lasting effect on skills.

A potential threat for identification in our analysis, as in previous similar studies, concerns the mortality of weak foetuses due to adverse weather conditions. In fact, to the extent that rainfall shocks increase foetal mortality, the population of new-borns included in our sample would include those who survived to the shock. If this were the case, the effect of the in-utero-shock would be underestimated (Andalon et al., 2016). While the magnitude of the potential bias cannot be established, we argue that our estimates would represent a lower bound of the real effect of rainfall shock in-utero.

Moreover, the relatively reduced sample of YL might represent a limitation. For instance, it might be that the estimated statistically insignificant effects on cognitive and non-cognitive skills are the product of a lack of statistical power. However, the longitudinal feature of the YL data and the fact that it includes several measures of children's skills represent an important advantage of this dataset in comparison to cross-sectional or administrative datasets with larger sample sizes.

Climate change and other negative shocks (e.g., pandemics) are likely to happen more often in the future. Given the importance of skills in determining educational, labour, and social outcomes, and the importance of early skills development, policies should be designed to protect maternal welfare during pregnancy. This could be through cash or in-kind (e.g., food) transfers for mitigate the impacts of the shock on the household wealth but also offering psychological support to mothers who are dealing with the stress and anxiety caused by the shock during the delicate phase of pregnancy.

References

Ahmed, S., & Ray, R. (2017). Do In Utero Shocks Have Adverse Effects on Child Health Outcomes and Can Welfare Schemes Ameliorate Such Effects? Evidence from Andhra Pradesh, India. *Journal of Biosocial Science,* 50(6), 770-799. https://doi.org/10.1017/S0021932017000591

Ahmed , Z, , D. R. Mohan Rao, K.R. Mohan Reddy and Y. E. Raj (2013), Urban Flooding: Case of Hyderabad, Global Journal of Engineering, Design and Technology, Vol 2 (4):63-66.

Aizer, A., Stroud, L., & Buka, S. (2016). Maternal Stress and Child Outcomes: Evidence from Siblings. *The Journal of human resources*, 51(3), 523-555. https://doi.org/10.3386/w18422

Almlund, M., Duckworth, A.L., Heckman, J.J., & Kautz, T.D. (2011). Personality and Psychology Economics. In E. Hanushek, S. Machin, and L. Woessman, eds., *Handbook of the Economics of Education*. (pp. 1-181). Amsterdam.

Almond, D. (2006). Is the 1918 Influenza Pandemic Over? Long-term Effects of In Utero Exposure in the Post-1940 U.S. Population*. Journal of Political Economy*, 114(4), 672-712. https://doi.org/10.1086/507154

Almond, D., & Currie, J. (2011). Killing Me Softly: The Fetal Origins Hypothesis. *Journal of Economic Perspectives*, 25 (3), 153-72. https://doi.org/10.1257/jep.25.3.153

Almond, D., & Mazumder, B. (2011). Health Capital and Prenatal Environment: The Effect of Ramadan Observance During Pregnancy. *American Economic Journal: Applied Economics,* 3, 56 – 85. https://doi.org/10.1257/app.3.4.56

Almond, D., Mazumder, B., & Ewijk, R. (2015). In utero Ramadan Exposure and children's academic performance. *The Economic Journal*, 125, 1501 – 1533. https://doi.org/10.1111/ecoj.12168

Amare, M., Jensen, N.D., Shiferaw, B., & Cissé, J.D. (2018). Rainfall Shocks and Agricultural Productivity: Implication for Rural Household Consumption. *Agricultural Systems*, 166, 79–89.

Andalon, M., Azevedo, J.P., Rodriguez-Castelan, C., Sanfelice, V., & Valderrama-Gonzalez, D. (2016). Weather Shocks and Health at Birth in Colombia. *World Development*, 82, 69 – 82. https://doi.org/10.1016/j.worlddev.2016.01.015

Andersen, S.L. (2003). Trajectories of brain development: point of vulnerability or window of opportunity? *Neuroscience & Biobehavioral Reviews,* 27(1–2), 3-18. https://doi.org/10.1016/s0149-7634(03)00005-8

Attri, S.D., & Tyagi, A. (2010). Climate Profile of India. Met Monograph No. Environment Meteorology-01/2010. Published by Environment Monitoring and Research Centre. India Meteorological Department. India (New Delhi).

Austin, M.P., Hadzi-Pavlovic, D., Leader, D., Saint, K., & Parker, G. (2005) Maternal trait anxiety, depression and life event stress in pregnancy: relationships with infant temperament. *Early Human Development*, 81(2):183–190. [PubMed: 15748973]

Adhvaryu, A., Nyshadham A., Molina T., & Tamayo, J. (2018) Helping children catch up: early life shocks and the PROGRESA experiment. NBER Working Paper series 24848.

Baez, J. E., Caruso, G., & Niu, C. Tracing Back the Weather Origins of Human Welfare. Evidence from Mozambique. *Policy Research Working Paper,* No. 8167. World Bank Group.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist, 28*, 117-148. https://doi.org/10.1207/s15326985ep2802_3

Banerjee, A., Duflo, E., Postel-Vinay, G., and Watts, T. (2010). Long-run Health Impacts of Income Shocks: Wine and Phylloxera in Nineteenth-Century France. *The Review of Economics and Statistics*, 92(4), 714—728. https://doi.org/10.1162/REST_a_00024

Barker, D.J. (1990). The fetal and infant origins of adult disease. *British Medical Journal*, 301, 1111. doi: https://doi.org/10.1136/bmj.301.6761.1111

Barker, D.J. (1998). In utero programming of chronic disease. Clinical Science (London, England, 1979), 95(2), 115-28. https://doi.org/10.1042/cs0950115

Bharadwaj, P., Eberhard, J.P., & Neilson, C. (2018), Health at Birth, Parental Investments, and Academic Outcomes. *Journal of Labor Economics,* 36 (2), 349 - 394, https://EconPapers.repec.org/RePEc:ucp:jlabec:doi:10.1086/695616.

Bhavani, P., V. Chakravarthi, P. S. Roy, P. K. Joshi, and K. Chandrasekar. 2017. “Long-Term Agricultural Performance and Climate Variability for Drought Assessment: A Regional Study from Telangana and Andhra Pradesh States, India.” Geomatics, Natural Hazards and Risk 8(2):822–40.

Bladimir Carrillo, 2020. Early Rainfall Shocks and Later-Life Outcomes: Evidence from Colombia. *World Bank Economic Review*, World Bank Group, vol. 34(1), pages 179-209.

Block, J. (1995). A contrarian view of the five-factor approach to personality description. *Psychological Bulletin,* 117(2), 187–215. https://doi.org/10.1037/0033-2909.117.2.187

Borghans, L., Duckworth, A.L., Heckman, J.J., and ter Weel, B. (2008). The Economic and Psychology of Personality Traits. *The Journal of Human Resources*, 43(4), 972-1059, University of Wisconsin Press, https://doi.org/10.3368/jhr.43.4.972

Bundervoet, T., & Fransen, S. (2018). The educational impact of shocks in utero: Evidence from Rwanda. *Economics and Human Biology*, 29, 88—101. https://doi.org/10.1016/j.ehb.2018.01.005

Cameron, L., & Shah, M. (2015). Risk Taking Behaviour in the Wake of Natural Disasters, *The Journal of Human Resources,* 50(2), 2484-515. https://doi.org/10.3368/jhr.50.2.484

Carrillo, B. (2020). Early Rainfall Shocks and Later-Life Outcomes: Evidence from Colombia. *World Bank Economic Review*, World Bank Group, 34(1), 179-209.

Chatterjee, J., & Merfeld, J.D. (2020). Protecting Girls from Droughts with Social Safety Nets *IZA Discussion Paper No*. 13694. Bonn.

Cunha, F., & Heckman, J. (2008). Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation. *The Journal of Human Resources, 43*(4), 738-782. https://doi.org/10.3368/jhr.43.4.738

Cunha, F., Heckman, J.J., and Schennach, S.M. (2010). Estimating the Technology of Cognitive and Noncognitive Skill Formation. *Econometrica*, 78(3), 883—931. https://doi.org/10.3982/ECTA6551

Conti, G., Hanson, M., Inskip, H., Crozier, S., Cooper, C., & Godfrey, K. (2020). Beyond birthweight: The origins of Human Capital. IZA Working Paper, No. 13296.

Cueto, S., & Leon J. (2012) Psychometric characteristics of cognitive development and achievement instruments in round 3 of Young Lives. Young Lives Technical Note No. 25.

Cueto, S., Leon J., Guerrero G., & Muñoz I. (2009). Psychometric characteristics of cognitive development and achievement instruments in round 2 of Young Lives. Young Lives Technical Note No. 15.

Datar, A., Liu, J., Linnemayr, S., & Stecher, C. (2013). The impact of natural disasters on child health and investments in rural India. *Social science & medicine (1982)*, 76(1), 83–91. https://doi.org/10.1016/j.socscimed.2012.10.008

De, U.S., Dube, R.K., & Prakasa Rao, G.S. (2005). Extreme Weather Events over India in the past 100 Years. *Journal of Indian Geophysics Union*, 9(3), 173-187.

Dillon, A., McGee, K., & Oseni, G. (2015). Agricultural Production, Dietary Diversity and Climate Variability. *The Journal of Development Studies*, 51(8):976–95.

Dinkelman, T. (2017). Long-run Health Repercussions of Drought Shocks: Evidence from South African Homelands. *The Economic Journal*, 127, 1906-1939. https://doi.org/10.1111/ecoj.12361

DiPietro, K., M. Voegtline. (2017). The gestational foundation of sex differences in development and vulnerability. *Neuroscience*, 3422017, 4-20.

Dunn, L. M., & Dunn, L. M. (1997). *Peabody picture vocabulary test-III*. Circle Pines, MN: American Guidance Service.

Fletcher, J.M. (2018). The effects of in-utero exposure to the 1918 influenza pandemic on family formation. *Economics and Human Biology*, 30, 59-68. https://doi.org/10.1016/j.ehb.2018.06.004

Glewwe, P., Jacoby, H.G., & King, E.M. (2001). Early childhood nutrition and academic achievement: a longitudinal analysis. *Journal of Public Economics*, 81(3), 345—368. https://doi.org/10.1016/S0047-2727(00)00118-3

Guhathakurta, P., Sanap, S., Menon, P., Prasad, A.K., Sangwan, N., and Advani S.C. (2020). Observed Rainfall Variability and Changes over Andhra Pradesh state. Published by Government of India. Ministry of Earth Sciences. India Meteorological Department.

Guttman, N.B. (1999): Accepting the Standardized Precipitation Index: a calculation algorithm. Journal of the American Water Resources Association, 35(2):311–322

Heckman, J.J., Stixrud, J., & Urzua, S. (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics*, 24(3), 412-482. https://doi.org/10.1086/504455

Hoddinott, J. (2006). Shocks and their consequences across and within households in rural Zimbabwe. *Journal of Development Studies*, 42(2), 301–321. https://doi.org/10.1080/00220380500405501

Jerusalem, M., & Schwarzer, R. (1992). Self-efficacy as a resource factor in stress appraisal processes. In R. Schwarzer (Ed.), *Self-efficacy: Thought control of action* (p. 195–213). Hemisphere Publishing Corp.

Judge, T. A., Locke, E. A., & Durham, C. C. (1997). The dispositional causes of job satisfaction: A core evaluations approach. *Research in Organizational Behavior,* 19, 151–188

Judge, T. A.; Erez, A.; Bono, J. E. (1998). *"The power of being positive: The relation between positive self-concept and job performance". Human Performance*. **11** (2–3), 167–187. https://doi.org/10.1080/08959285.1998.9668030

Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2002). Are measures of self-esteem, neuroticism, locus of control, and generalized self efficacy indicators of a common core construct? *Journal of Personality and Social Psychology*, 83, 693–710. https://doi.org/10.1037/0022-3514.83.3.693

Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2003). The Core Self-Evaluations Scale (CSES): Development of a measure. Personnel Psychology, 56**,** 303-331. https://doi.org/10.1111/j.1744-6570.2003.tb00152.x

Judge, T. A., & Hurst, C. (2007). The benefits and possible costs of positive core self-evaluations: A review and agenda for future research. D. Nelson & C. L. Cooper (Eds.), Positive organizational behavior (pp. 159-174). London, UK: Sage Publications. http://dx.doi.org/10.4135/9781446212752.n12

Knudsen, E.I. (2004). Sensitive Periods in the Development of the Brain and Behavior. *Journal of Cognitive Science*, 16(8), 1412—1425. https://doi.org/10.1162/0898929042304796

Krishnan, R., Sanjay, J., Gnanaseelan, C., Mujumdar, M., Kulkarni, A., & Supriyo Chakraborty (2020), Assessment of Climate Change over the Indian Region. A Report of the Ministry of Earth Sciences (MoES). Government of India.

Krutikova, S., & Lilleor, H.B. (2015). Fetal Origins of Personality: Effects of early life circumstances on adult personality traits. CSAE Working Paper.

Kumar, S., Molitor, R., & Vollmer, S. (2014). Children of Drought: Rainfall Shocks and Early Child Health in Rural India, No 1407, Working Papers, Sam Houston State University, Department of Economics and International Business. https://EconPapers.repec.org/RePEc:shs:wpaper:1407

Kumra, N. (2008), "An Assessment of the Young Lives Sampling Approach in Andhra Pradesh, India", Young Lives Technical Note No. 2, March 2008.

Leon, J., & Singh, A. (2017). Equating test scores for receptive vocabulary across rounds and cohorts in Ethiopia, India and Vietnam. *Young Lives Technical Note* (40).

Linnet KM, Wisborg K, Agerbo E, Secher NJ, Thomsen PH, Henriksen TB. (2006). Gestational age, birth weight, and the risk of hyperkinetic disorder. *Arch Dis Child*, 91(8), 655-60. doi: 10.1136/adc.2005.088872. PMID: 16754656; PMCID: PMC2083047.

Lloyd-Hughes, B. & Saunders, M. A. (2002). A drought climatology for Europe. *International Journal of Climatology*, 22,1571-1592. https://doi.org/10.1002/joc.846

Lo Bue, M.C., (2019). Early Childhood during Indonesia's Wildfires: Health Outcomes and Long-Run Schooling Achievements. *Economic Development and Cultural Change*, University of Chicago Press, 67(4), 969-1003. DOI: 10.1086/700099

Matsuura, K., & Willmott, C.J. (2015). Terrestrial Precipitation: 1900-2014 Gridded Monthly Time Series. Version 4.01. http://climate.geog.udel.edu/~climate/html_pages/Global2014/README.GlobalTsP2014.html

Maccini, S., & Yang, D. (2009). Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall. *American Economic Review*, 99(3), 1006 – 1026. https://doi.org/10.1257/aer.99.3.1006

Majid, M.F. (2015). The persistent effects of an in utero nutrition shocks over the life cycle: Evidence from Ramadan fasting. *Journal of Development Economics*. 117 Issue C, 48 – 57. https://doi.org/10.1016/j.jdeveco.2015.06.006

Mara, D. (2003). Water, Sanitation and Hygiene for the Health of Developing Nations. *Public Health*, 117(6), 452–456. doi: 10.1016/S0033-3506(03)00143-4

McKee, T. B., Doesken, N., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. Preprints, 8th Conference on Applied Climatology, 179-84.

Meier L.L., Orth U., Denissen J.J.A., & Kuhnel A. (2011). Age differences in instability, contingency, and level of self-esteem across the life span. *Journal of Research in Personality*. 45(6), 604–612. https://doi.org/10.1016/j.jrp.2011.08.008

Miguel, E., & Kremer, M. (2004). Worms: Identifying impacts on education and health in the presence of treatment externalities. *Econometrica*, 72(1), 159—217.

Mount, M. K.; Barrick, M. R. (1995). The Big Five personality dimensions: Implications for research and practice in human resources management. *Research in Personnel and Human Resources Management*, 13, 153–200.

Mulmi P, Block SA, Shively GE, Masters WA. Climatic conditions and child height: Sex-specific vulnerability and the protective effects of sanitation and food markets in Nepal. Econ Hum Biol. 2016 Dec;23:63-75. doi: 10.1016/j.ehb.2016.07.002. Epub 2016 Jul 22. PMID: 27494247; PMCID: PMC5147727.

Neelsen, S., and Stratmann, T. (2012). Early-Life Famine Exposure and Later-Life Outcomes: Evidence from Survivors of the Greek Famine. GMU Working Paper in Economics No. 12-02. https://doi.org/10.2139/ssrn.1986723

Palanisami, K., Haileselassie, A., Reddy, K. K., Ranganathan, C. R., Wani, S. P., Craufurd, P., & Kumar, S. (2015). Climate Change, Gender and Adaptation Strategies in Dryland Systems of South Asia. A Household Level Analysis In Andhra Pradesh, Karnataka and Rajasthan States of India. Hyderabad: International Crops Research Institute for Semi-Arid Tropics.

Rooij, S. R., Wouters, H., Yonker, J. E., Painter, R. C., & Roseboom, T. J. (2010). Prenatal undernutrition and cognitive function in late adulthood. *Proceedings of the National Academy of Sciences of the United States of America*, 107(39). https://doi.org/16881–16886. 10.1073/pnas.1009459107

Rosales-Rueda M. (2018). The impact of early life shocks on human capital formation: evidence from El Niño floods in Ecuador. *J Health Econ*. 62,13-44. doi: 10.1016/j.jhealeco.2018.07.003.

Rosales, M.F. (2014). Impact of Early Life Shocks on Human Capital Formation: El Nino Floods in Ecuador. *IDB Working Paper Series,* No. IDB-WP-503. Inter-American Development Bank (IDB).

Rose, E. (1999). Consumption Smoothing and Excess Female Mortality in Rural India. *Review of Economics and Statistics* 81(1):41–49.

Rosenberg, M. (1965). Society and the Adolescent Self-Image. Princeton, NJ: Princeton University Press. https://doi.org/10.1126/science.148.3671.804

Rosenfeld, C.S. (2015). Sex-Specific placental responses in fetal development. *Endocrinology* 156 (10), 3422–3434.

Rotter, J.B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychol Monogr Gen Appl*, 80(1): 1–28. https://doi.org/10.1037/h0092976

Rocha, R., & Soares, R.R. (2015). Water scarcity and birth outcomes in the Brazilian semiarid. *Journal of Development Economics*, 112, 72—91. https://doi.org/10.1016/j.jdeveco.2014.10.003

Sanchez, A. (2017). Early-life exposure to weather shocks and human capital accumulation. Evidence from the Peruvian Highlands. *Young Lives Working Paper, No. 178*. Young Lives, Oxford.

Schwarzer, R., & Jerusalem, M. (1995). Generalized Self-Efficacy scale. In J. Weinman, S. Wright, & M. Johnston, *Measures in health psychology: A user's portfolio. Causal and control beliefs* (pp. 35-37). Windsor, UK: NFER-NELSON.

Shah, M., & Steinberg, B.M. (2017). Drought of Opportunities: Contemporaneous and Long-term Impacts of Rainfall Shocks on Human Capital. *Journal of Political Economy*, 125, 2. https://doi.org/10.1086/690828

Shenkin SD, Starr JM, Deary IJ. (2004). Birth weight and cognitive ability in childhood: a systematic review. *Psychol Bull.*, 130(6), 989-1013. doi: 10.1037/0033-2909.130.6.989. PMID: 15535745.

Skoufias, E., & Vinha, K. (2012). Climate variability and child height in rural Mexico. *Economics and Human Biology*, 10(1), 54—73, https://doi.org/10.1016/j.ehb.2011.06.001

Skoufias, E., & Vinha, K. (2013). The impacts of climate variability on household welfare in rural Mexico. *Population and Environment*, 34(3), 370–399. https://doi.org/10.1007/s11111-012-0167-3

Spears D. (2012). Height and cognitive achievement among Indian children. *Economics and Human Biology*, 10 (2), 210-9. doi: 10.1016/j.ehb.2011.08.005. Epub 2011 Aug 25. PMID: 21907646.

Stiles, J., & Jernigan, T.L. (2010). The Basics of Brain Development. *Neuropsychology Review*, 20(4), 327—348. https://doi.org/10.1007/s11065-010-9148-4

Thai, T.Q., & Falaris, M.E. (2014). Child Schooling, Child Health, and Rainfall Shocks: Evidence from Rural Vietnam. *Journal of Development Studies*, 50(7), 1025-1037, https://doi.org/10.1080/00220388.2014.903247

Thompson, R.A., & Nelson, C.A. (2001). Developmental science and the media. Early brain development. *American Psychologist, 56*(1), 5–15. https://doi.org/10.1037/0003-066X.56.1.5

Walsh, K., McCormack, C.A., Webster, R., Pinto, A., Lee, S., Feng, T., Krakovsky, H.S., O'Grady, S.M., Tycko, B., Champagne, F.A., Werner, E.A., Liu, G., & Monk, C. (2019). Maternal prenatal stress phenotypes associate with fetal neurodevelopment and birth outcomes. *PNAS*, 116 (48), 23996-24005. https://doi.org/10.1073/pnas.1905890116

Webb, D. (2019). Critical Periods in Cognitive and Socioemotional Development: Evidence from Weather Shocks in Indonesia. *Economics and Finance.* ffdumas-02407565f

Yamashita, N., & Trinh, T. (2020). The Effects of Prenatal Exposure to Plentiful Rainfall on Cognitive Development in Viet Nam. ERIA *Discussion Paper,* No. 353. Economic Research Institute for ASEAN and East Asia.

Young Lives. (2017). Young Lives Survey Design and Sampling (Round 5); United Andhra Pradesh. Young Lives Factsheet. October 2017.

Yorke, L., and Ogando Portela, M.J. (2018). Psychosocial Scales in the Young Lives Round 4 Survey. Selection, Adaptation and Validation. Technical Note 45. Young Lives. University of Oxford.

Appendix

Table A1: Definitions of non-cognitive skill items used

Agency: Individual's sense of agency or mastery over his/her own life

1) I have no choice about the work I do
2) If I study hard, I will be rewarded with a better job in the future
3) I like to make plans for my future studies and work
4) Other people in my family make all the decisions about how I spend my time
5) If I try hard, I can improve my situation in life

Self-esteem (Rosenberg Scale): Individuals' judgement of their own self-value or self-worth

1) I do lots of important things
2) In general, I like being the way I am
3) Overall, I have a lot to be proud of
4) I can do things as well as most people
5) Other people think I am a good person
6) A lot of things about me are good
7) I'm as good as most other people
8) When I do something, I do it well

Generalised Self-efficacy Scale: One's belief in their capabilities to produce given attainments and to cope with adversity

1) I can always manage to solve difficult problems if I try hard enough.
2) If someone opposes me, I can find the means and ways to get what I want.
3) It is easy for me to stick to my aims and accomplish my goals.
4) I am confident that I could deal efficiently with unexpected events.
5) Thanks to my resourcefulness, I know how to handle unforeseen situations.
6) I can solve most problems if I invest the necessary effort.
7) I can remain calm when facing difficulties because I can rely on my coping abilities.
8) When I am confronted with a problem, I can usually find several solutions.
9) If I am in trouble, I can usually think of a solution.
10) I can usually handle whatever comes my way.

Core Self-evaluation: Core self-evaluation is a trait that reflects an individual's evaluation of their abilities and own control (Judge et al., 1998). It is predicted from a principal factor analysis of the agency scale, self-esteem scale and generalised self-efficacy scale, all standardised to mean zero and standard deviation of one.

Figure A1: Inter-annual variability in rainfall during 1900-2014 in the Young Lives communities (Average yearly rainfall 1900 - 2014)

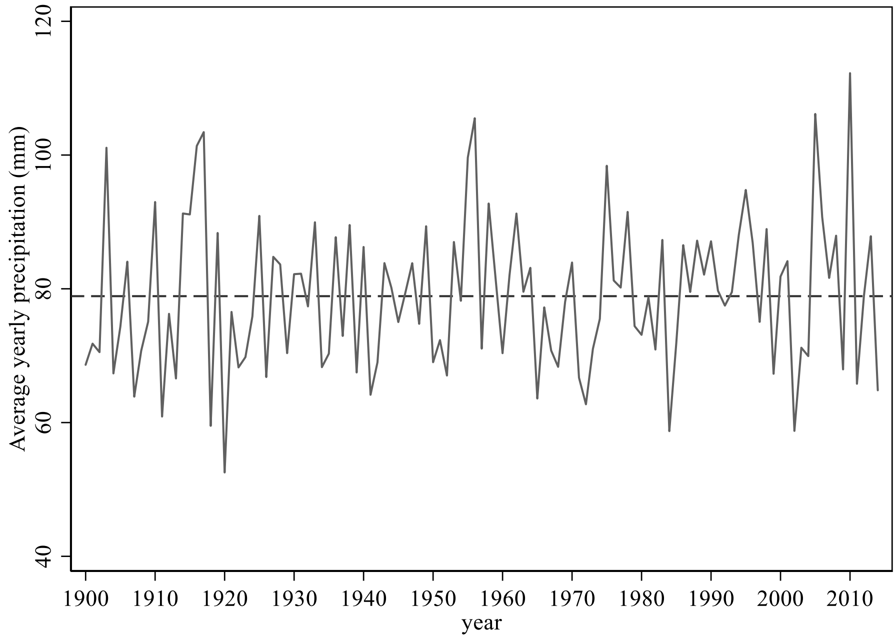


Figure A2: Date of birth distribution

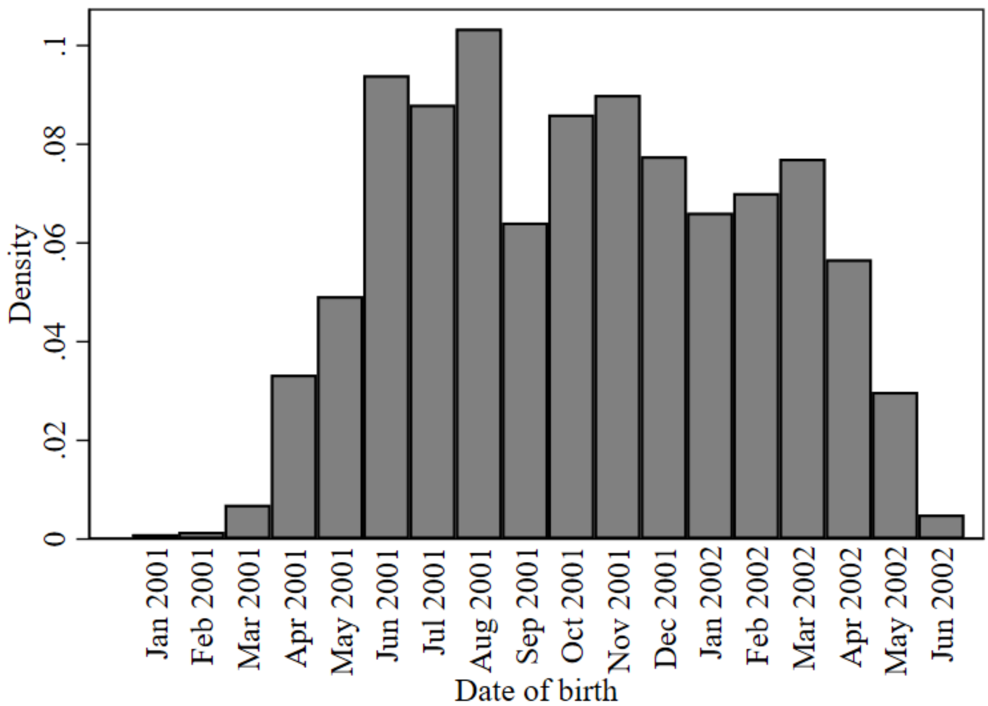


Table A2: Maternal and household characteristics of children born or not born in monsoon season

	Born in monsoon		Not born in monsoon		T-test	Obs.
	Mean	SE	Mean	SE	p-value	
Mother's education						
Incomplete primary or less	0.72	0.018	0.71	0.014	0.565	1732
Completed primary or up to completed secondary	0.25	0.017	0.27	0.013	0.456	1732
Tertiary education and above	0.02	0.006	0.02	0.004	0.638	1732
Urban location	0.23	0.017	0.23	0.013	0.948	1732
Mother's height	151.38	0.232	151.62	0.185	0.439	1717
Mother's age (years)	24.11	0.180	23.51	0.129	0.006	1728
Number of older siblings	0.72	0.039	0.73	0.031	0.724	1732
Number of older sisters	0.51	0.038	0.52	0.030	0.864	1732
Number of older brothers	0.45	0.037	0.47	0.029	0.789	1732
Ethnicity						
Scheduled Caste	0.16	0.015	0.15	0.012	0.715	1732
Scheduled Tribe	0.48	0.015	0.46	0.011	0.595	1732
Backward Caste	0.20	0.020	0.20	0.015	0.831	1732
Other	0.72	0.016	0.73	0.012	0.724	1732

Note: SE = Standard error. The sample is constrained to children whose background characteristics are observed, and at least one of their skills score (PPVT, mathematics or CSE) is measured in all rounds. The p-values for a t-test for differences in means between control group and the treated groups are reported in the second column.

Table A3: The effect of in-utero rainfall shocks on children's skills (historical period: 1950 - 2002)

	PPVT IRT	Math IRT	CSE
Age 5	-0.139*		
	(0.077)		
Age 8	-0.004	2.830	
	(0.072)	(5.809)	
Age 12	-0.077	-1.043	0.027
	(0.092)	(5.982)	(0.081)
Age 15	-0.078	-9.494	-0.158*
	(0.126)	(6.362)	(0.081)
N	1,313	1,697	1,315

Note: Historical period defined using monthly rainfall data for the period 1950-2002. All specifications control for child's age, gender, and caste, year-of-birth fixed-effects, month-of-birth fixed effects, and community fixed-effects. Standard errors are clustered at the community level. The sample is constrained to children of whom their skills scores are observed at all ages. P-values to show if the estimate is statistically significant from zero is indicated by $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A4: In-utero rainfall shocks on children's skills, by child's gender

	PPVT IRT		Math IRT		CSE	
	Male	Female	Male	Female	Male	Female
Age 5	-0.326**	0.004				
	(0.127)	(0.129)				
Age 8	-0.104	-0.035	-3.782	4.174		
	(0.109)	(0.128)	(7.832)	(8.990)		
Age 12	-0.096	-0.100	-12.316	5.664	0.057	-0.022
	(0.132)	(0.139)	(7.794)	(8.682)	(0.105)	(0.137)
Age 15	-0.242	-0.160	-15.236**	-14.169	-0.049	-0.252
	(0.163)	(0.173)	(7.168)	(10.697)	(0.112)	(0.163)
N	687	626	912	785	711	604

Note: All specifications control for child’s age in the specified round, gender, and caste, year-of-birth fixed-effects, month-of-birth fixed-effects, and community fixed-effects. Standard errors are clustered at the community level. The sample is constrained to children of whom their skills scores are observed in every age. P-values to show if the estimate is statistically significant from zero is indicated by *p < 0.1, **p < 0.05, ***p < 0.01.

Table A5: In-utero rainfall shocks on children's skills, by highest parental education

	PPVT IRT		Math IRT		CSE	
	Less than completed primary education	Completed primary and above	Less than completed primary education	Completed primary and above	Less than completed primary education	Completed primary and above
Age 5	-0.140	-0.125				
	(0.111)	(0.151)				
Age 8	-0.107	0.043	-9.786	15.930*		
	(0.109)	(0.114)	(9.725)	(8.157)		
Age 12	-0.147	0.039	-6.644	5.937	0.138	0.009
	(0.148)	(0.135)	(10.846)	(8.049)	(0.120)	(0.116)
Age 15	-0.248	-0.055	-24.825**	0.697	-0.239**	-0.091
	(0.200)	(0.196)	(11.363)	(8.874)	(0.119)	(0.106)
N	761	552	862	835	653	662

Note: All specifications control for child's age in the specified round, gender, and caste, year-of-birth fixed-effects, month-of-birth fixed-effects, and community fixed-effects. Standard errors are clustered at the community level. The sample is constrained to children of whom their skills scores are observed in every age. P-values to show if the estimate is statistically significant from zero is indicated by *p < 0.1, **p < 0.05, ***p < 0.01.

Table A6: The effect of in-utero rainfall shocks by frequency, on children's skills at age 5,8,12 and 15

		PPVT IRT	Math IRT	CSE
Age 5	1 shock	-0.157**		
		(0.072)		
	2 shocks	-0.117		
		(0.109)		
	≥3 shocks	-0.073		
		(0.169)		
F-test, 1 shock = 2 shocks = ≥3 shocks		0.134		
F-test, 1 shock = 2 shocks		0.875		
F-test, 1 shock = ≥3 shocks		0.184		
F-test, 2 shocks = ≥3 shocks		0.669		
Age 8	1 shock	-0.051	0.354	
		(0.073)	(5.952)	
	2 shocks	0.033	5.326	
		(0.121)	(8.904)	
	≥3 shocks	0.092	-1.729	
		(0.154)	(10.473)	
F-test, 1 shock = 2 shocks = ≥3 shocks		0.555	0.772	
F-test, 1 shock = 2 shocks		0.662	0.439	
F-test, 1 shock = ≥3 shocks		1.061	0.050	
F-test, 2 shocks = ≥3 shocks		0.287	1.247	
Age 12	1 shock	-0.078	-3.965	0.079
		(0.089)	(5.609)	(0.075)
	2 shocks	-0.018	5.603	0.081
		(0.135)	(8.958)	(0.114)
	≥3 shocks	0.222	17.802	0.193
		(0.158)	(11.771)	(0.170)
F-test, 1 shock = 2 shocks = ≥3 shocks		3.108**	2.028	0.325
F-test, 1 shock = 2 shocks		0.410	1.618	0.000
F-test, 1 shock = ≥3 shocks		5.485***	3.854*	0.500
F-test, 2 shocks = ≥3 shocks		4.982***	1.409	0.629
Age 15	1 shock	-0.127	-14.212**	-0.150*
		(0.119)	(6.149)	(0.081)
	2 shocks	-0.106	-3.987	-0.337***
		(0.165)	(9.364)	(0.115)
	≥3 shocks	0.098	5.429	-0.121
		(0.257)	(14.766)	(0.168)
F-test, 1 shock = 2 shocks = ≥3 shocks		0.565	1.247	2.367*
F-test, 1 shock = 2 shocks		0.028	1.783	3.630*
F-test, 1 shock = ≥3 shocks		1.040	2.075	0.039
F-test, 2 shocks = ≥3 shocks		1.031	0.687	2.355

N	1,313	1,697	1,315

Note: All specifications control for child's age in the specified round, gender, and caste, year-of-birth fixed-effects, month of birth fixed-effects, and community fixed-effects. Standard errors are clustered at the community level. The sample is constrained to children of whom their skills scores are observed in every age. The F-test reports the F-statistic when testing the joint significance that all coefficients are equal, as well as equality of coefficients between the categorical number of shocks. P-values to show if the estimate is statistically significant from zero (including the p-values for the F-test) is indicated by *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.