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ABSTRACT

The Origins of Cognitive Skills and Non-cognitive Skills: The Long-Term Effect of in-Utero Rainfall Shocks in India*

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. Also, shocks occurred after the first trimester are more detrimental for skills development. Our findings support the implementation of policies aiming at reducing inequalities at very early stages in life.

JEL Classification: J24, I14
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 & 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. More specifically, it exploits exposure to rainfall fluctuations to test: (i) whether exposure to environmental shocks during pregnancy negatively affects children's cognitive and non-cognitive skills development; (ii) whether the effects vary depending on the intensity of the shock; and (iii) whether the impacts of being exposed to shocks differ across pregnancy trimesters. 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 the effect of interest evolves 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. Our findings are therefore suitable to provide evidence for the design of policies aiming at minimizing the long-term impacts of milder shocks on the foetal environment.

We find that children who are exposed to rainfall shocks in-utero have lower cognitive skills at age 5 and age 15. In particular, we find that being exposed to at least a 1.5 standard deviation of rainfall shocks in-utero reduces the receptive vocabulary test score (as measured by the Peabody Picture Vocabulary Test - PPVT) at age 5 (in 0.13 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 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 0.15 points. No statistically significant effects were found between ages 8 and 12. Finally, according to our results, being exposed to shocks after the first trimester of pregnancy has the largest detrimental effects on children's cognitive scores.

The remainder of the paper is organized as follows. Section 2 briefly reviews previous studies on this topic. 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

[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

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

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.[5] 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.[6] 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 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. The authors argue that in prenatal months, the developing brain is vulnerable to external insults such as viral infection, alcohol exposure, and malnutrition, warranting attention to prenatal brain development. In addition, Andersen (2003) argues that there are potential periods of vulnerability during prenatal brain development which could, in turn, have important long-term effects on psychological and behavioural dysfunction, but research on this is still at its infancy. 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.

Economists have also 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

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[5] 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 effects of experience 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.

[6] Gestational week refers to the number of weeks post conception (from the mother's last menstrual cycle).

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 (2013) 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 weight of birth. 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).

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.[7]

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.

[7] 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.
[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, Locke, and Durham (1997). Individuals with high CSE think positively of themselves and are confident about their own abilities. Conversely, people with low CSE have a negative appraisal

[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).

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, which 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:

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

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

[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.

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] While the self-reported shocks do 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).

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

[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.
[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.

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:

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

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.

[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.

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.

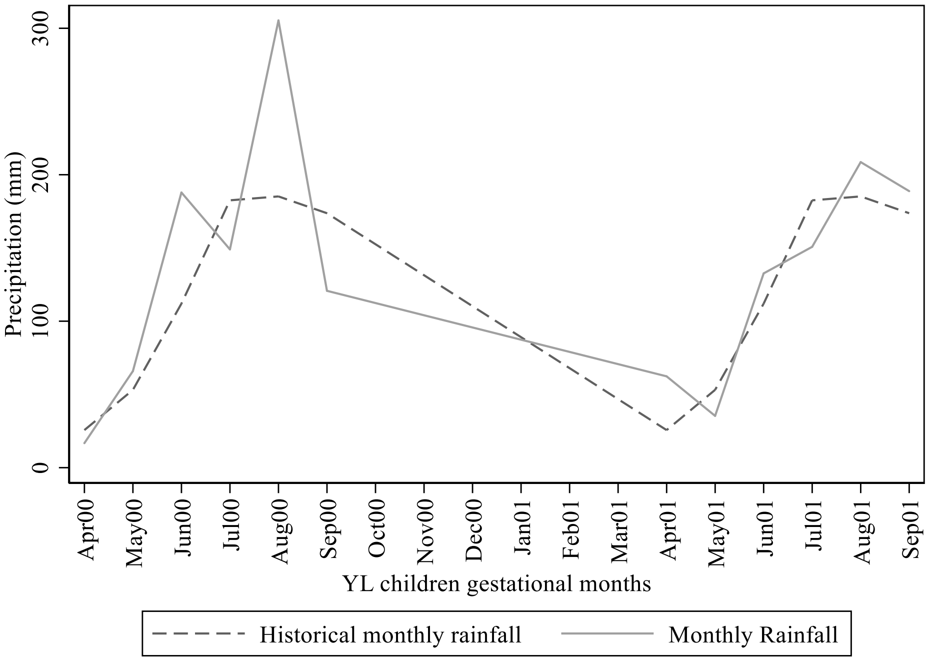
4 Rainfall shocks in India during the YL children in-utero period

The climate in India is typically characterised by four general seasons, winter in January and February, the pre-monsoon season between March and May, the monsoon rainy season between June and September when 75% of the annual rainfall occurs, and the post-monsoon period between October and December (Attri and Tyagi, 2010).

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

Figure *1* displays the average monthly-and-community specific historical rainfall registered across the 100 YL communities in India and the average monthly-and-community specific rainfall beginning from April 2000 up until September 2001, corresponding to the in-utero period of the YL children. 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 April. Furthermore, when comparing rainfall fluctuations during the in-utero period against the historical rainfall we observe that the monsoon season in 2000 (between June and August) shows particularly intense precipitations. This is likely due to the cyclone that hit Andhra Pradesh in August 2000 (De et al., 2005).

Figure 1: Average monthly rainfall and deviation from the historical mean during the in-utero period



Note: The monthly rainfall reported in the figure is computed averaging the monthly rainfall across the Young Lives communities for the period April 2000-September 2001. The historical monthly rainfall is the average monthly rainfall registered in each community during the period 1900-2014.

The YL communities are distributed across three agro-climatic regions: 42 communities are in Coastal Andhra, 33 in Telangana and 25 in Rayalaseema. Looking at the geographical distribution of the rainfall shocks during the in-utero period, we find that a larger proportion of communities are affected by positive shocks compared to negative shocks. The prevalence of rainfall shocks (flood and droughts) during the in-utero period is highest in Telangana communities, while Coastal Andhra and Rayalaseema communities are more prone to positive shocks compared to the communities in the other two regions.

Most children have been exposed to an abnormal amount of precipitation during the gestation period (Table 1). Three out of four children experienced at least a shock of 1.5SD during the gestation period. Furthermore, almost a third of the children (31%) have been exposed to extreme rainfall shocks during the gestation period (2SD or more). 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 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
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.

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 fifth column. Overall, we find that the exposure to in-utero shocks is homogeneously distributed across the selected subgroups. However, we find that children in rural areas are more likely to have been exposed to shocks in-utero compared to those in urban areas. Although these differences may suggest that children from less 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
Child's age (in months)	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 is urban	0.74	0.01	0.87	0.02	0.000
Parent characteristics					
Mother's education					
Incomplete primary or less	0.75	0.01	0.76	0.02	0.252
Completed primary and completed secondary	0.23	0.01	0.21	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	0.61	0.01	0.63	0.02	0.150
Completed primary and completed secondary	0.33	0.01	0.31	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 gestational 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). Premature births were self-reported by the mother, with 1,682 observations. The p-values for a t-test for differences in means between control group and the treated groups are reported in the second 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 age distribution is spread across 18 months, between January 2001 and June 2002 as described above.

We test for three 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, 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.

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

$$Y_{ijc,t} = \propto + \beta_0 S_{ijc} + \gamma C_j + \omega_c + year_i + \varepsilon_{ij,t} \quad (1)$$

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 gestational 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.[21] Finally, we include a year of birth fixed-effect to account for time trends. $\varepsilon_{ij,t}$ 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); and second, its timing (i.e., during which pregnancy trimester the first shock occurs).

[21] 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.

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.

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

In equation (3), 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 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}.

$$Y_{ijc,t} = \propto + \sum_{r=0}^{4} \varphi_r S_{ijc}^r + \delta T_{ijc} + \gamma C_j + \omega_c + year_i + \varepsilon_{ij,t} \tag{3}$$

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 A1 in the Annex, births are equally spread over time.[22] Also, 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; age; and, the number of children) in the two subgroups are largely similar, the only exception being the urban/rural place of residence, as in Table 2. 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.

[22] 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.

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 shocks in-utero reduces PPVT scores at age 5 (in 0.13 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 0.15 points.

Table 3: In-utero rainfall shocks on children's skills

	PPVT IRT	Math IRT	CSE
Age 5	-0.128*		
	(0.068)		
Age 8	-0.038	1.006	
	(0.072)	(5.820)	
Age 12	-0.059	-3.800	0.100
	(0.089)	(5.323)	(0.070)
Age 15	-0.114	-13.579**	-0.145*
	(0.113)	(5.663)	(0.078)
Observations	1313	1697	1315

Note: All specifications control for child's age, gender, and caste, year 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 4 shows evidence about the variation of the effects according to the intensity of the shock. It 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. We find that the exposure to strong shocks is driving the detrimental effect on children's PPVT score at age 5 while no effect is found for mild shocks. Conversely, being exposed to a mild shock negatively affects PPVT and CSE at age 15. Finally, both mild and strong shock have a (equal) negative impact on math score at age 15.

Table 4: In-utero rainfall shocks by intensity, on children's skills

		PPVT IRT	Math IRT	CSE
Age 5	≥1.5SD and <2SD	-0.117		
		(0.077)		
	2SD and above	-0.144*		
		(0.082)		
Age 8	≥1.5SD and <2SD	-0.060	-1.084	
		(0.094)	(6.486)	
	2SD and above	-0.005	3.763	
		(0.088)	(6.378)	
Age 12	≥1.5SD and <2SD	-0.130	-7.961	0.029
		(0.085)	(5.861)	(0.091)
	2SD and above	0.052	1.720	0.196*
		(0.121)	(6.991)	(0.102)
Age 15	≥1.5SD and <2SD	-0.234*	-14.753**	-0.168*
		(0.129)	(6.991)	(0.090)
	2SD and above	0.072	-12.029*	-0.114
		(0.125)	(6.255)	(0.094)
Observations		1313	1697	1315

Note: All specifications control for child's age in the specified round, gender, and caste, year 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.

We then explore whether the impacts of being exposed to rainfall shocks differ depending on whether the child was exposed to a rainfall shock for the first time in the first, second or third pregnancy trimester. Table 5 shows that being exposed to the first rainfall shock after the first trimester is most detrimental to children's cognitive scores. A rainfall shock experienced during the second trimester negatively affects PPVT scores at age 5 more than if the shock first occurred in the first or third trimester. Similarly, in-utero rainfall shocks during the second or third trimester negatively affect the math score while no effect is found for shocks occurring in the first trimester.

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	-0.151		
		(0.126)		
	2nd trimester	-0.223*		
		(0.130)		
	3rd trimester	-0.141		
		(0.123)		
Age 8	1st trimester	-0.127	10.187	
		(0.139)	(9.439)	
	2nd trimester	-0.145	10.851	
		(0.130)	(8.618)	
	3rd trimester	-0.071	3.887	
		(0.131)	(9.146)	
Age 12	1st trimester	-0.110	-14.543	0.008
		(0.140)	(11.255)	(0.154)
	2nd trimester	-0.087	-12.268	-0.012
		(0.137)	(8.862)	(0.122)
	3rd trimester	-0.188	-13.961	-0.041
		(0.123)	(9.384)	(0.123)
Age 15	1st trimester	-0.292	-18.510	-0.109
		(0.191)	(11.236)	(0.152)
	2nd trimester	-0.103	-19.862**	-0.050
		(0.183)	(9.785)	(0.139)
	3rd trimester	-0.223	-23.095**	-0.089
		(0.166)	(10.034)	(0.129)
Observations		1313	1697	1315

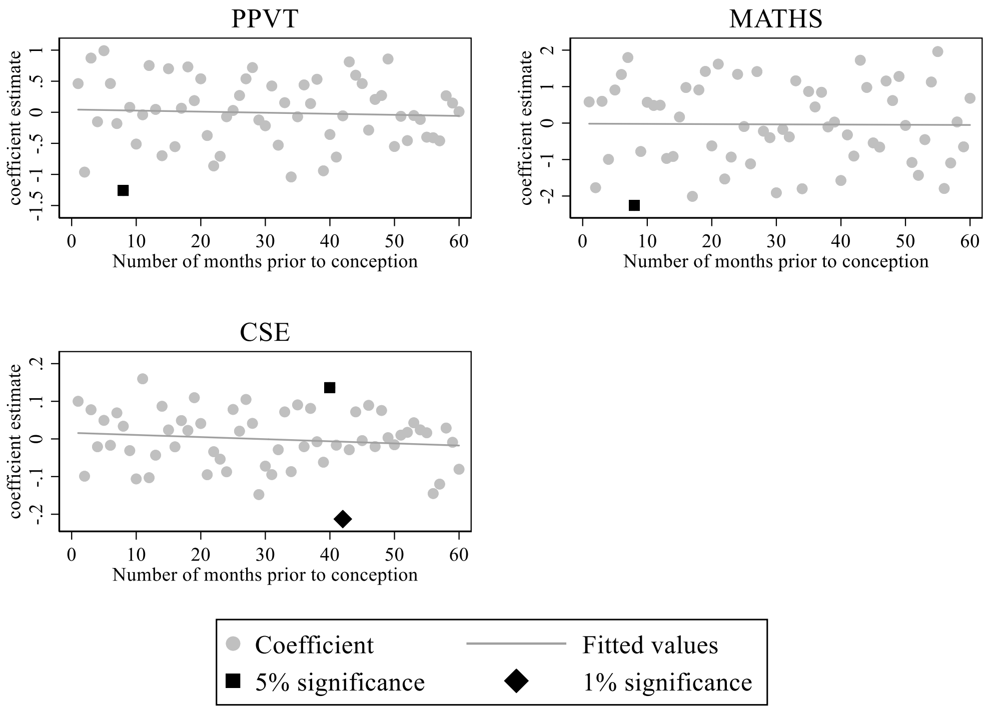
Note: 1st trimester is the gestation period between week 0—12, 2nd trimester is week 13 – 27, 3rd trimester is between week 28 – birth. All specifications control for child's age in the specified round, gender, and caste, total number of shocks that occurred in-utero, year of birth fixed-effects, and 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 $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

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 month before the child's conception date up to 5 years (or 60 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 month 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. Only few coefficients are significant. For mathematics and PPVT, we can see that there is only one negative estimate, significant at the 5% level at about 8-9 months before the conception date, and the rest of the estimates are statistically insignificant. For CSE, there is one positive estimate and one negative estimate close to the 40th month before the conception date, significant at the 5% and 1% respectively. Results from a multiple hypothesis testing confirm that the few significant effects shown in Figure 2 are false rejections of the null hypothesis about the effect of the shocks on skills.[23]

Figure 2: Estimates on exposure 0 to 5 years before conception on PPVT, Mathematics and CSE scores at age 15, by month



Note: The estimated coefficients correspond to separated specifications on each of the three scores at age 15 for each month before conception, 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.

[23] 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, and particularly after the first trimester, are detrimental to children's cognitive skills. We also provide new evidence that in-utero shocks reduce non-cognitive skills during adolescence.

The effect of rainfall shocks on foetus development might happen through different mechanisms: food availability (quantity and quality of mother's intakes), income (e.g., changes in labour demand), availability of health services (e.g., prenatal check-ups), psychological status (parental stress and anxiety), among others (Hoddinott, 2006; Maccini and Yang, 2009; Skoufias and Vinha, 2013; Aizer et al, 2016). Also, after birth, households might compensate and invest more in skills development if they perceived a child was negatively affected by a shock in-utero. 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 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. (2018). 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. doi:10.1017/S0021932017000591

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., and Kautz, T.D. (2011). Personality and Psychology Economics. In E. Hanushek, S. Machin, and L. Woessman, eds., Handbook of the Economics of Education, Amsterdam: Elsevier. pp. 1-181. (2011)

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, vol. 114(4), 672—712.

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

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.

Almond, D., Mazumder, B., & Ewijk, R. (2015). In utero Ramadan Exposure and children's academic performance. The Economic Journal. 125. pp. 1501 – 1533.

Andalon, M., Azevedo, J.P., Rodriguez-Castelan, C., Sanfelice, V., & Valderrama-Gonzalez, D. (2016). Weather Shocks and Health at Birth in Colombia. World Development, Vol, 82, pp. 69 – 82.

Andersen, S.L. (2003). Trajectories of brain development: point of vulnerability or window of opportunity? *Neuroscience & Biobehavioral Reviews*, 27(1–2), 3-18,

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist, 28*, 117-148.

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, vol. 92(4): 714—728.

Barker, D.J. (1990). The fetal and infant origins of adult disease. *British Medical Journal*, *301 (6761), 1111*.

Barker, D.J. (1998). In utero programming of chronic disease. Clinical Science (London, England, 1979), 95(2), 115-28.

Block, J. (1995). A contrarian view of the five-factor approach to personality description. *Psychological Bulletin, 117*(2), 187–215.

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. University of Wisconsin Press, vol. 43(4).

Bundervoet, T., & Fransen, S. (2018). The educational impact of shocks in utero: Evidence from Rwanda. Economics and Human Biology, vol.29, p.88—101.

Cameron, L., Shah, M., 2013. Risk Taking Behaviour in the Wake of Natural Disasters. NBER Working Paper Series, No. 19534. Cambridge, MA

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.

Cunha, F., Heckman, J.J., and Schennach, S.M. (2010). Estimating the Technology of Cognitive and Noncognitive Skill Formation. Econometrica, vol. 78(3), 883—931.

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.

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), 16881–16886.

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, vol. 9(3), 173—187.

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, vol. 30, p.59—68.

Heckman, J.J., Stixrud, J., and Urzua, S. (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. Journal of Labor Economics, vol. 24(3), 412—482.

Hoddinott, J. (2006). Shocks and their consequences across and within households in rural Zimbabwe. Journal of Development Studies, 42(2), 301–321.

Attri, S.D., and 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).

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.; 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.*

Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2002). Are measures of self-esteem, neuroticism, locus of control, and generalized selfefficacy indicators of a common core construct? Journal of Personality and Social Psychology, 83, 693–710

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.

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.

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

Knudsen, E.I. (2004). Sensitive Periods in the Development of the Brain and Behavior. Journal of Cognitive Science, vol. 16(8), 1412—1425.

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

Kumar, Santosh, Molitor, Ramona and Vollmer, Sebastian, (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.

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

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

Lloyd-Hughes, B. & M. A. Saunders, 2002. A drought climatology for Europe. *International Journal of Climatology*, 22:1571-1592.

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.

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. Vol. 117, issue C. pp. 48 – 57.

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

Meier LL, Orth U, Denissen JJA, 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.

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.*

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.

Rosenberg, M. (1965). Society and the Adolescent Self-Image. Princeton, NJ: Princeton University Press.

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

Rocha, R., & Soares, R.R. (2015). Water scarcity and birth outcomes in the Brazilian semiarid. Journal of Development Economics, 112:72—91.

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 vol. 125. No.2.

Skoufias, E., & Vinha, K. (2013). The impacts of climate variability on household welfare in rural Mexico. Population and Environment, 34(3), 370–399.

Stiles, J., & Jernigan, T.L. (2010). The Basics of Brain Development. Neuropsychology Review, vol. 20(4), 327—348.

Thompson, R.A., & Nelson, C.A. (2001). Developmental science and the media. Early brain development. *American Psychologist, 56*(1), 5–15.

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.

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, DOI: 10.1080/00220388.2014.903247

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. Date of birth distribution

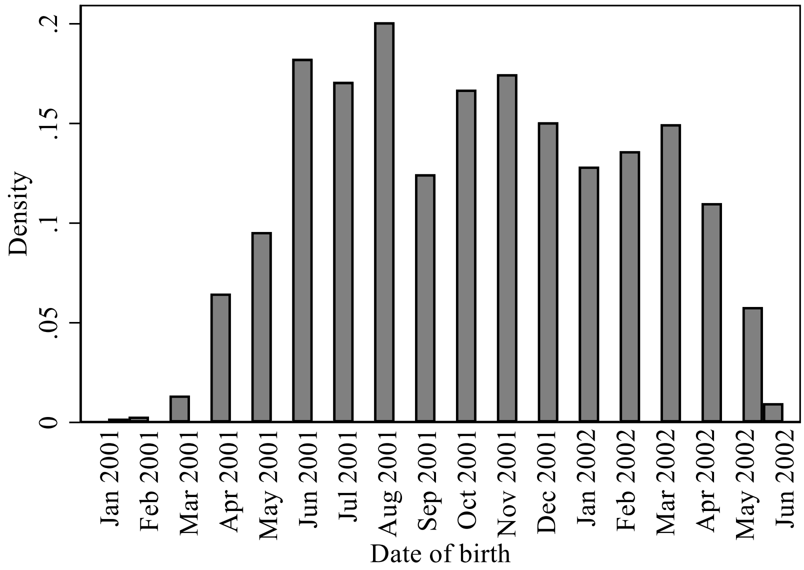


Table A2. Maternal and household characteristics of children born or not in monsoon season

	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	0.02	0.71	0.01	0.565	1732
Completed primary & up to completed secondary	0.25	0.02	0.27	0.01	0.456	1732
Tertiary education and above	0.02	0.01	0.02	0.00	0.638	1732
Urban location	0.23	0.02	0.23	0.01	0.23	1732
Mother's height	151.38	0.23	151.62	0.19	151.38	1717
Mother's age (years)	24.11	0.18	23.51	0.13	24.11	1728
Number of older siblings	0.72	0.04	0.73	0.03	0.72	1732
Number of older sisters	0.51	0.04	0.52	0.03	0.86	1732
Number of older brothers	0.45	0.04	0.47	0.03	0.79	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.