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**Abstract**[1]

Global warming is changing precipitation patterns, harming communities strongly tied to agricultural production, particularly in low-and-middle income countries (LMICs). Whilst the long-term effects of being exposed to rainfall shocks early in life on school achievement tests are well-established, there is little population-based evidence from LMICs on the mechanisms through which these shocks operate. This paper analyses the effects of early exposure to rainfall shocks on four foundational cognitive skills (FCSs), including executive functions (EF) that have been found to be key predictors of educational success. These skills were measured via a series of tablet-based tasks administered in Peru as part of the Young Lives longitudinal study (YLS). We combine the YLS data with gridded data on monthly precipitation to generate monthly, community-level rainfall estimates. The key identification strategy relies on temporary climatic shocks being uncorrelated with other latent determinants of FCS development. Our results show significant negative effects of early life exposure to rainfall shocks on EF. We also find evidence of rainfall shocks decreasing households' abilities to invest in human capital, which may affect both FCS and domain-specific test scores. Interestingly, social policies providing affected households with additional resources partially offset the effects of the rainfall shocks.

**Keywords:** Skills formation, Human capital, Rainfall, Peru, Early childhood
**JEL Codes:** J24, Q54, I24, I14

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## 1. Introduction

Despite considerable progress in recent years, undernutrition among children is still highly prevalent in low- and middle-income countries (LMICs). An estimated 249 million children under 5 years of age are at risk of not being able to realize their developmental potential, with the primary indicator for 170 million of these being undernutrition, as evidenced by stunting (Black et al., 2017; Lu et al., 2016). Climate change is partially responsible for slowing down the long secular declines in undernutrition, as it is rapidly increasing weather variation causing more unpredictable precipitation patterns (USGCRP, 2017). This unpredictability especially affects LMIC communities that are economically tied to agricultural production and that often lack access to good irrigation and water-management systems. Children from these communities are particularly vulnerable in their early years to economic shocks, which often have long-term consequences for their human-capital formation (Almond et al., 2018).

The long-term implications of early life exposure to rainfall shocks on health and nutrition (Dimitrova & Muttarak, 2020; Randell et al., 2020; Hirvonen et al., 2020; Skoufias & Vinha, 2012), and on school domain-specific achievement tests and educational attainments (Maccini & Yang, 2009; Thai & Falaris, 2014; Randell & Gray, 2019; Hyland & Russ, 2019) are fairly well-established.[2] However, to our knowledge, there is little population-based evidence from LMICs about the mechanisms through which climate shocks may lead to poorer domain-specific achievement-test performance and educational outcomes, making it difficult to inform remediating policies.

This paper contributes toward addressing this gap by investigating the long-term impacts of exposure to rainfall shocks during the first 1,000 days of life on foundational cognitive skills (FCS), which may be important mechanisms through which climate shocks could affect domain-specific achievements. We use unique data collected through the administration of series of tablet-based tasks included in the Rapid Assessment of Cognitive and Emotional Regulation, RACER (Behrman et al., 2022; Hamoudi & Sheridan, 2015). We collected these data as part of the Young Lives Study (YLS), one of only a handful of LMIC cohort studies that can be used for life-course analysis over infancy, childhood and adolescence, and the only one with data on FCS, rarely available in large sample surveys in LMICs. RACER includes tasks to measure inhibitory control (i.e., the capacity to control attention or behaviour and override counterproductive impulses); working memory (i.e., the capacity to hold in mind and manipulate information not visible in the environment); long-term memory (i.e., the capacity to encode, retain, and retrieve information) and implicit learning (i.e., the capacity to learn without conscious awareness).

[2] Skills such as reading, arithmetic, or linguistics, are domain-specific, as they relate to specific types of knowledge. In contrast, domain-general skills, such as inhibitory control or working memory, are linked to the accumulation of knowledge across multiple domains (Hamoudi & Sheridan, 2015).

Both inhibitory control and working memory are components of executive functioning (EF), a specific group of mental capacities required to formulate goals, plan how to achieve these goals and carry-out these plans effectively (Lezak, 1982). EF is increasingly found to be a key domain of child development and a key predictor of educational success. For example, some studies link EF to school readiness, more so than IQ, entry level reading or math skills (Fernald et al., 2009; Blair and Razza, 2007; Blair, 2002). Other studies find that individuals with higher EF are less likely to engage in risky behaviours related to health and crime. Furthermore, the existing evidence shows that EF is highly associated with early-life household socio-economic status and with investments by parents and teachers (Noble et al., 2005, 2007; Farah et al., 2006; Klenberg et al., 2001; Ardila et al., 2005), suggesting that EF is malleable, at least during childhood, and not predetermined at birth. Stressful, challenging, or deprived conditions may impede the development of these skills and hasten their decay (Lupien et al., 2009; Shonko & Garner 2012; Nelson & Sheridan, 2011; McLaughlin et al, 2014; Sheridan & McLaughlin, 2014; Sheridan et al., 2012, 2013). The periods of development span well into the second decade of life for working memory and inhibitory control, both of which are key elements of EF.

Many of the existing studies on EF or, more generally, FCS, have focused on high-income countries (HICs), as opposed to LMICs, where arguably children are at greater risk of not reaching their developmental potential and wherein live the vast majority of the world's children (Black et al., 2017; Lu et al., 2016). Furthermore, most evidence comes from experimental studies with (often very) small samples. Climate shocks, which have been shown to have an impact on schooling achievement, might also have an impact on FCS and EF. However, to our knowledge, this potential connection is yet to be analysed.

For our analysis, we combine the YLS child-level data with gridded estimates of monthly total precipitation across land surfaces from the Matsuura and Wilmott (2015) dataset. We use the grid points for the YLS communities to create monthly, community-level rainfall estimates and construct the Standard Precipitation Index (SPI) (Lloyd-Hughes & Saunders, 2002). We adopt the conventional measure of rainfall shocks as a deviation of rainfall from the historical averages, during the crop-growing rainy season (defined as the four months with the highest average rainfall, at the community level), for the same locality, and during the same period.

We exploit rainfall fluctuations to investigate whether: (i) the exposure to climatic shocks early in life negatively affects FCS measured in adolescence; (ii) the magnitude of the impact on FCS depends on when the shock was experienced, either during the gestational period or the first two years of life, and on the nature of the shock (abnormally high or abnormally low rainfall). Further, we investigate some potential mechanisms through which the shocks could have affected FCS, by (iii) testing whether the negative effects of shocks are stronger for children growing-up in agricultural households as opposed to households that do not rely on agriculture as the main source of income, (iv) exploring potential effects on other indicators of human-capital accumulation (mainly height-for-age and vocabulary) for which we have data from earlier in their lives; and (v) analysing the effects on households' food security. Finally, (vi) we explore the potential remediation role of social policies by analysing heterogeneous effects on children from the JUNTOS conditional-cash-transfers (CCT) program.

The key identification strategy relies on the assumption that temporary climatic shocks, are uncorrelated with other latent determinants of FCS development. Our identification strategy uses community fixed effects to control for unobserved time-invariant characteristics common to all children in the same community, alongside year- and month-of-birth fixed effects to control for events that might have an impact across all children born during the same year or in specific calendar months. Importantly, our strategy relies on the presence of data for sibling pairs, providing additional variation in the timing and nature of early life rainfall shocks: the YLS index children who were all born over a 12-month period and were between 12 and 13 years old at the time RACER was implemented, and their younger siblings who were between 6 and 12 years old at this time.

Our results show robust negative effects of rainfall shocks on FCS and particularly on working memory and inhibitory control. The gestational period is particularly sensitive to these shocks, with abnormally low and high rainfall shocks appearing to affect FCS equally. Furthermore, our results provide some evidence on the reduction of households' incomes as a potential mechanism through which rainfall shocks affect FCS. Specifically, rainfall shocks seem to affect the abilities of households to invest in their children's nutrition. We hypothesise that these changes in income are related to reductions in agricultural output in the region, although we do not find any differentiated effects for agricultural households. Finally, we find evidence suggesting that there is space for public policies providing monetary relief to remediate for the negative effects of rainfall shocks on FCS.

The rest of the paper is organized as follows: section 2 briefly summarizes the existing literature on the impact of rainfall shocks on educational attainment and domain-specific learning outcomes; section 3 outlines the conceptual framework; section 4 and section 5 describe, respectively, the data and the empirical strategy used for the study; section 6 presents the main results; section 7 includes an exploration of some of the potential mechanisms behind the relationships uncovered between rainfall shocks and FCS; section 8 concludes.

## 2. Literature review

*2.1 The impact of rainfall shocks*

The long-term implications of early life exposure to rainfall shocks on educational attainments are fairly well-established. Maccini & Yang (2009) evaluate the impact of rainfall deviations (from local means) during early childhood in Indonesia, and find that higher rainfall during the year of birth leads to higher schooling attainment for women, but no effects for men, nor for shocks after or prior to birth years. The authors argue that the result is driven by the positive impact of rainfall on agricultural output. Similarly, Thai & Falaris (2014) find that higher rainfall (above the commune-of-birth average), during the year of birth and the third year of life, shortens school-entry delays and enables faster progression through school in Vietnam. Randell & Gray (2016) find that an increase in rainfall during the summer agricultural season in rural Ethiopia is associated with an increase in the probability of completing at least one year of school and attending school at the time of the interview for children affected during their first seven years of life. Hyland & Russ (2019) use DHS data for women in 19 countries in sub-Saharan Africa and find that being exposed to droughts (measured as a Standardized Precipitation Index, SPI lower than -1.5) during early childhood has negative effects on schooling attainment, adult heights and wealth (for women from rural households only). Some studies also note that there is a nutrition-learning link that is triggered by climate shocks. For example, Alderman et al. (2006) use droughts as an instrumental variable to measure the effects of height-for-age on school grades completed.

Rainfall shocks do not affect everyone equally. Some studies only find effects for women (Maccini & Yang, 2009) and others find effects on rural households only (Hyland & Russ, 2019). These mixed results reflect different contexts and channels through which climate shocks affect human-capital accumulation. It is argued that exposure to rainfall shocks during the school period could lead to positive effects on education if it helps shift resources to increase investment in children's human capital. Shah & Steinberg (2017) find that, for children aged 5 to 16, droughts in India affect children's educational attainment positively, as—they argue—they push children away from agricultural work. Randell & Gray (2019) present another case of mixed results. Using census data for 29 countries in the Global South, they find that experiencing droughts during the gestational period and in early childhood is associated with lower schooling attainment for children in Southeast Asia, and northern and central Africa, but associated with more schooling attainment for children in Central America and the Caribbean.

There is less abundant evidence on the impact of climate shocks on cognitive achievement, as generally measured by domain-specific test scores. Rosales-Rueda (2018) exploits the *El Niño* phenomenon in Ecuador to show evidence of the effects of early life exposure to excessive rainfall (floods) on the

Peabody Picture Vocabulary Test (PPVT). More recently, Chang et al. (2022) use the YLS data to evaluate the long-term effects of in-utero rainfall shocks (droughts and floods) on domain-specific achievement tests in India. They find negative long-lasting effects on math (at age 15), but only short-term effects on vocabulary as measured by PPVT.

Overall, the existing literature uncovers a negative effect of rainfall shocks on schooling attainment and domain-specific cognitive-achievement test scores, although the magnitudes (and sometimes the directions) of the effects vary significantly and differ across different population subgroups. However, evidence on the impact of climate shock on domain-general cognitive skills is lacking. Furthermore, with few exceptions (Rosales-Rueda, 2018; Chang et al., 2022), the literature has emphasized the role of droughts, either explicitly (e.g., Hyland & Russ, 2019) or implicitly by analysing the role of the total amount of rainfall — but not excessive rain — in countries and/or time periods where the population is prone to droughts (e.g., Maccini & Yang, 2009).

*2.2 How climate shocks affect cognitive skills*

The existing literature suggest that climate shocks may affect cognitive skills through two main mechanisms: directly by affecting cognitive functioning (for example altering brain chemistry, electrical properties and function) or indirectly by affecting human-capital-accumulation processes (altering investments in relevant inputs of human-capital production). Most evidence on the direct effects comes from the medical literature,[3] while evidence on indirect effects comes predominantly from the economic literature, and documents the effect of environmental shocks, in terms of child health, nutrition and cognition (Dercon & Porter, 2014; Berhane et al., 2014; Baez et al., 2009). This paper contributes to this second stream of literature and the rest of this section briefly summarizes the main related evidence.

One clear way in which rainfall shocks could affect investment in human-capital accumulation is through income. An excess or lack of rainfall could have impacts on agricultural output (Felkner et al., 2009), which could directly affect the income and consumption of agricultural households (Dercon, 2004; Jayachandran 2006; Amare et al. 2018). However, non-agricultural households could also be impacted (Rijkers & Söderbom, 2013; Grabrucker & Grimm, 2021), as a decrease in agricultural outputs could increase food prices, or decrease food availabilities in markets and the intakes of important nutrients. Additionally, abnormally high or low levels of rainfall could affect other sources of income either directly linked to agriculture and food prices (wholesale and retail trade, transportation,

[3] For example, studies suggest that elevated temperatures affect completing complex cognitive tasks (Fine & Kobrick, 1978; Hocking et al., 2001; Park, 2017) and diminish attention, memory, information retention and processing (Vasmatzidis et al., 2002)

restaurants), or not directly linked to agriculture (i.e., construction, destruction of infrastructure), and through changes in the general equilibrium (i.e., less money spent on services).

Overall, decreases in households' incomes may directly affect children's nutritional intakes, which, in turn, may limit healthy development and growth (Nicholas et al., 2021; Dimitrova & Muttarak, 2020; Cornwell & Inder, 2015; Skoufias & Vinha, 2012). The existing evidence suggests that poor nutritional status is associated with lower FCS (Sánchez et al., 2022). These impacts are particularly relevant during the first 1,000 days of life, a period in which shocks are more prone to affect the long-term acquisition of cognitive skills, as widely recognized in the nutritional and economic literature (Victora et al., 2008; Maluccio et al., 2009; Victora et al. 2010; Almond et al., 2018).

## 3. Conceptual framework

Following closely Todd & Wolpin (2003), and Glewwe & Miguel (2007), we consider a framework in which the first 1,000 days (the in-utero period plus the first two years after birth) is taken as period *t*=1, and the remainder of childhood as period *t*=2. In period *t*=1, family of child *i* can invest in cognitive skills ($S_{1,i}$), as follows:

$$S_{1,i} = f_1(F_{1,i}^S, F_{1,i}^H, S_{0,i}) \qquad (1)$$

Where $F_{1,i}^S$ denote family inputs of an educational nature in period 1; $F_{1,i}^H$ are health-related family inputs in period 1; and $S_{0,i}$ is the cognitive endowment. Following an analogous structure, cognitive skill in period 2 ($S_{2,i}$) can be expressed by the history of inputs invested in the child:

$$S_{2,i} = f_2(F_{2,i}^S, F_{1,i}^S, F_{2,i}^H, F_{1,i}^H, S_{0,i}) \qquad (2)$$

Here, $F_{2,i}^S$ and $F_{2,i}^H$ represent investments in period 2. For simplicity of exposition, we assume parents are altruistic so that they gain utility from their children's cognitive skills in addition to their own consumption.[4] The utility function for family *i* can be expressed for the one-child case as:

$$U_i = f(C_{1,i}, C_{2,i}, S_{1,i}, S_{2,i}) \qquad (3)$$

where $C_{t,i}$ is parental consumption in period *t*. Resources to pay for family inputs and consumption in each period *t* come from household income in that period ($I_{t,i}$) with, for simplicity, no transfer of

[4] Alternatively, or in addition, parents may be interested in their children's cognitive skills because the expected support the children can provide to the parents in their old age increases in their children's skills.

budgetary resources across periods. We assume household income is negatively correlated with rainfall shocks ($\theta$), and the prices of inputs $p$ are positively correlated with rainfall shocks, under the usual assumption that markets in LMICs tend to be segmented and only weakly linked to national and international markets.

$$I(\theta)_{t,i} = p(\theta)_{c,t}C_{t,i} + p(\theta)_{H,t}F_{t,i}^{S} + p(\theta)_{S,t}F_{t,i}^{H} \qquad (4)$$

Within this framework, parents are expected to choose optimally for inputs $F_{t,i}^{S}, F_{t,i}^{H}$, and consumption $C_{t,i}$ over $t = 1, 2$, subject to constraints (1) to (4). This framework is highly simplified (for example, the roles of parental time and community inputs are not incorporated) but seeks to illustrate that, as is commonly observed in poor LMIC households, household incomes and input prices are prone to be affected by rainfall shocks. For this reason, the occurrence of rainfall shocks can lead to reduced investment in cognitive skills in period 1, which are transferred to the next period by the inclusion of lagged inputs in the cognitive production function for period 2 in equation 2.

Of course, this simple model does not consider that households may have ways of coping with shocks. For example, households could use their savings, sell assets (i.e., livestock) or access credit markets to mitigate short-term shocks. In the context of LMICs, poor households usually have little savings and face constraints to access credit markets. However, it is possible that strategies of this type are used to mitigate the effects of the shocks and, sometimes, can successfully limit some of the negative effects of rainfall shocks on cognitive skills. Thus, it is possible that the effects observed in our study are less pronounced than they otherwise would be due to these strategies.

Other mitigation strategies, particularly relevant in the context of households involved in agriculture, include finding other sources of income outside of the agricultural sector, or investing more time working at the farm. These other strategies could still result in decreases in inputs for cognitive skills, as they could force caregivers into the labour market at times that are crucial for children's development. In terms of the model, caregivers' hours spent working implies fewer hours invested in providing inputs into child development, $F_{1,i}^{S}$ or $F_{1,i}^{H}$.

All of these strategies have the peculiarity that, even if they help mitigate the negative effects of the shock by increasing income $I(\theta)_{t,i}$, they do nothing to reduce the size of the impact $\theta$, which might still affect prices. However, there are some other coping mechanisms that could lessen the effects of rainfall shocks on input and consumption prices. In the case of higher agricultural input prices created by shocks that reduce agricultural outputs, agricultural households could potentially mitigate these effects by shifting their production to more resilient products (either more water-resistant or less water-dependent). This is only possible in a given crop year if the rainfall shock arrives before the beginning of production. To account for this possibility, we are only considering rainfall shocks happening during the rainy season, which works as a proxy for the period in which most crop-choice decisions should have already been made[5]. Similarly, we consider the intensity of the shocks by measuring the total number of months in which shocks were experienced during rainy seasons, as multiple rainfall shocks should be harder to prevent or mitigate.

## 4. Data

### 4.1 The Young Lives study

The YLS is a longitudinal research study on childhood poverty that follows 12,000 children in four countries: Ethiopia, India (Andhra Pradesh and Telangana), Peru and Vietnam. The first survey took place in 2002 with four further rounds of in-person data collection in 2006/07 (Round 2), 2009/10 (Round 3), 2013/14 (Round 4) and in 2015/2016 (Round 5). For the empirical analysis, we use a sample of 1,511 children (index children) who were born in Peru in 2001—2002 and were aged between 6 to 18 months in the first survey round. In addition, we use information on a sample of 605 younger siblings, aged 2 to 8 years in 2009/10, the first time they were interviewed. The RACER tool designed to measure FCS was administered to both cohorts in Round 4 (2013/14) only.

In all rounds, a child questionnaire, including data on child health, anthropometrics and education, and a household questionnaire, including data on caregiver background, livelihood, household composition, socio-economic status, shock were administered. In addition, test scores in vocabulary and math were collected since Round 2 (2006/07). In the siblings' sample, key characteristics, such as anthropometrics and test scores, were collected since Round 3 (2009/10).

The index children were enrolled from 74 communities within 20 selected districts that were randomly selected from the whole universe of Peruvian districts (excluding the wealthiest 5%). After districts were chosen, a community or housing block was randomly selected, and then all dwellings from each cluster of houses were visited to look for children of the right ages. Once a block was completely examined, and if the desired sample size was not met, the next available neighbouring block was visited by the fieldworker, following the same process. This process was followed until the desired sample size was met. The final sample represents the poorest 95% of children from both urban and rural areas in

[5] It is worth noting that there are other production decisions that could be made after the crop-choice and could potentially mitigate the effects of the shock, mainly regarding the use of certain inputs such as fertilizers. For agricultural households, these decisions imply a reallocation of the household's resources to buy such inputs, which could in turn still affect the amount resources assigned to the child's development.

the three main geographical regions: coast, highland (altiplano) and jungle. More information on the sampling strategy can be found in Escobal et al. (2003).

Although the YLS samples are not nationally representative, comparisons with DHS data show they cover the diversity of children in Peru (Escobal & Flores, 2008). The proportion of rural households is 55% and average mothers' schooling attainment is less than seven grades. The attrition rate across the first four survey rounds that we use is 6.3%, which is relatively low compared to other longitudinal studies. To achieve such low levels of attrition, the study successfully followed most sample families that moved within the country (Sánchez & Escobal, 2020). Table 1 presents descriptive statistics of the sample.

**INSERT TABLE 1 HERE**

### 4.2 Measurements of FCS

Data on FCS were collected for both index children and their siblings during Round 4 (2013). At that time, the index children were aged 11 to 12 years, whereas the younger siblings were aged 5 to 11. The FCS were measured using a series of computer-based tasks through Rapid Assessment of Cognitive and Emotional Regulation (RACER) (Hamoudi & Sheridan, 2015; Ford et al., 2019; Behrman et al. 2022).[6] RACER is a novel touch-screen computer/tablet application that uses five short tasks (one to four minutes each) to assess four components of FCS (Inhibitory Control- IC, Working Memory- WM, Long-term Memory- LTM, and Implicit Learning- IL) in children aged 6 years and older (and adults). RACER was administered to 98.5% of the YLS sample available for interviews. Each assessment included in RACER is designed to be as domain-general as possible (e.g., performance should not be affected by literacy or numeracy) and at the same time as skill-specific as possible (Hamoudi & Sheridan, 2015). To achieve this goal, in each case performance is measured though a baseline task and a challenge task. The former is affected by factors such as the ability to understand instructions or familiarity with the use of digital devices, whereas the latter is designed to measure the same factors and the specific skills of interest (thus, to measure a specific skill, the baseline task results need to be controlled).

Table 2 summarizes the baseline and challenge tasks calculated in each case, and the average performance. LTM is measured by the proportion of correct answers, IC and WM by response times, and IC by a linear combination of response time and accuracy. Children who perform better in LTM

[6] More information about RACER and the FCS measured in the YLS can be found in Hamoudi and Sheridan (2015) and Behrman et al. (2022).

are expected to have a larger proportion of correct answers, while in the IC, IL or WM tasks children who perform better are expected to require less time. Similarly, those that perform better in WM would provide more accurate answers. To facilitate the interpretation of the results (such that a higher score is linked to better performance) we use an inverse function for our measurements of IC, IL and WM, and all variables are standardized by age in years.[7] This transformation allows us to directly interpret higher values as higher skills. In the case of the baseline tasks, they differ depending on the outcome variable. For IC, the baseline task consisted of a linear combination of two variables with the same weight (0.5): the average Euclidean distance for all same-side trials and the average response time for same-side trials. In the case of WM, LTM and IC, the baseline trials are composed of only one component, as described earlier. More information about the administration of RACER in the YLS sample can be found in Behrman et al. (2022).

**INSERT TABLE 2 HERE**

### 4.3 Rainfall data

Rainfall data are obtained from the University of Delaware, a commonly used climate dataset (see, for instance, Shah & Steinberg (2017), Rocha & Soares (2015), and Thai & Falaris (2014)). These data contain gridded estimates of monthly total precipitation across land surfaces between 1900 and 2017 (Matsuura & Wilmott, 2015). Each of the values is a local point estimate at a 0.5-degree of longitude-latitude resolution, based on publicly available observation-station records.

The rainfall data are used to compute the monthly historical means in each of the 82 YLS communities in Peru.[8] Using the grid points for which rainfall data are available, the rainfall data are matched to the GPS locations of the YLS communities (using the main square in each community as the reference point) (Mcquade & Favara, 2022).[9]

For each community, the monthly rainfall precipitation is calculated as a distance-weighted average of the monthly rainfall registered at the four closest grid points to that community. The weights used are computed as the inverse of the distances of the grid points from the community over the total inverse distance of all four grid points. This approach puts greater significance on grid points closer to the community.

[7] For standardization, we use the combined sample of all children in Ethiopia and Peru.

[8] Communities within YLS are defined as administrative areas, as these are geographically well-defined and recognised areas.

[9] For any communities that do not have main squares, another reference points are used, such as schools, churches, or post offices.

We then use these data to create the Standardized Precipitation Index (SPI), following Lloyd-Hughes & Saunders (2002). The main reason for using SPI data instead of direct rainfall data is because rainfall data are not usually normally distributed, as they are naturally truncated when reaching zero litters of rain. The SPI normalises the data, making both positive and negative shocks equally represented. We calculate the SPI for every community using data from the last 50 years. We use a 2.0 standard deviation from the historical means to define a rainfall shock.

As discussed, a potential channel through which climate shocks could affect FCS is through impacts on agricultural outputs, which, in turn, may have impacts on both agricultural and non-agricultural households. For this reason, our analysis focuses on shocks during the months in which rainfall variation might have had the largest effect on agricultural outputs. Typically, the rainy-season months are key for agriculture, as a big part of the agricultural outputs destined for national consumption is produced by small farmers with limited access to irrigation and heavily dependent on rain. Therefore, we only consider those rainfall shocks that occur during rainy-season months, defined as the four months with the highest average monthly rainfall in each community.

### 4.4 Defining rainfall shocks in the pre-natal and early childhood period

We initially define a shock as any monthly SPI deviation of at least 2 standard deviations above (*abnormally high rainfall shocks* or *floods*) or below (*abnormally low rainfall shocks* or *droughts*) the historical monthly average for the same community during each rainy-season month. The main specification of this study does not distinguish between abnormally high or abnormally low shocks, under the assumption that both an excess or a shortage of rainfall, when unpredicted, should negatively impact agricultural production. Here, we assume previous decisions and investments have been made with the expectation of average rainfall for that community. Later, we relax this assumption and we test the heterogenous impact of floods and droughts.

Information about the date and place of birth of each YLS child is used to identify the first 1,000 days of life, critical for human-capital development, and to distinguish between rainfall shocks that occurred during the gestational period (in-utero and/or pre-natal) and shocks that occurred during the early childhood period (the first and second years after birth).

The date of conception and the gestational period of each YLS child is defined using their date of birth and assuming 38 weeks (266 days) as an approximation of a normal-term pregnancy, as per the World

Health Organization definition.[10] Under these assumptions, the index children in our sample were conceived between March 2000 and October 2022, while the younger siblings were conceived between September 2002 and March 2007. We do not account for premature births when defining the gestational period. However, our estimations include (as a control) an indicator variable capturing whether a child was born prematurely, based on self-reported information from the children's mothers. In total, 25% of the children were born prematurely. Shocks happening during the in-utero period occurred from one to nine months before the month of birth. Our definition of gestational period encompasses the whole in-utero period for most children; but might include some additional time for those born prematurely. Hence, we are not making a difference between the in-utero period and the gestational period, and simply defining them as the same time-period. For the early childhood period, we consider shocks during the month of birth and the following 23 months as shocks during the first and second years of life. As we are only considering shocks occurring during the rainy season months, the maximum number of shocks during these periods is four for the in-utero period, and eight for the early childhood period.

### 4.5 Sample definition

To accurately impute exposure to rainfall shocks during the first 1,000 days given the available data, we restrict the sample to households that had not moved from the community where the index child was born before Round 3 (2009), which accounts for 79% of the sample. To do this, we proceed as follows: First, in order to identify the community of residence of the mother during the gestational period, we use Round 1 information on where the child was living at the time of the interview and information about how long the mother has been living in the same community.[11] Second, 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 any children whose mothers reported living in the Round-1 community for less than 9 months prior to the interview. Third, we restrict the sample to children from families that did not migrate up to Round 3. This allows us to define the community of residence during the relevant periods. We discuss potential issues of sample selectivity in Section 8.

The final subsample of non-migrant families from agricultural communities includes a total of 2,656 children, with 1,511 index children and 610 younger siblings. The final sample covers 82 communities, distributed across all three natural regions (coast, highland, and jungle).

[10] The World Health Organization defines preterm as giving birth before 37 weeks of pregnancy are completed. See the WHO website: https://www.who.int/news-room/fact-sheets/detail/preterm-birth. However, most papers use 266 days or 38/40 weeks as the threshold to define pre-term births.

[11] For younger siblings, we use information from Rounds 2 (2006) and 3 (2009) to guarantee that children did not move during their in-utero period and early childhood.

## 4.6. Rainfall shocks in the Peruvian Young Lives sites

Table 3 presents descriptive statistics for the number of shocks experienced by the children in our sample. We distinguish by type of shock (all shocks, abnormally high rainfall shocks and abnormally low rainfall shocks), period of exposure (first 1,000 days, in-utero period and first two years of life), for all children, index children and younger siblings.

**INSERT TABLE 3 HERE**

As observed, abnormally high shocks are more prevalent than abnormally low shocks during the relevant time periods. More shocks are experienced during the post-birth period than during the gestational period. This is an expected result, as the post-birth period rainy season includes eight months over 24 months, whereas the in-utero period rainy seasons include only between one and four rainy-season months.

It is also worth noting that there are many children that never experience a shock. To have a better idea of how prevalent exposure is and how the shocks are distributed, Table 4 reports the percentages of children who experience at least one shock and the average number of shocks for those experiencing at least one shock.

**INSERT TABLE 4 HERE**

In total, 27% of children experience at least one shock during the first 1,000 days of life. For this 27%, we observed that on average children experience almost two shocks during their first 1,000 days of life. This contrasts with the average presented in Table 4. Most children subjected to at least one shock experienced an abnormally high shock, especially during the first or second year of life. As with the averages, the proportion of index children experiencing shocks is higher than the proportion of siblings. In particular, only a minority of the siblings experienced at least one shock within the in-utero period.

# 5. Empirical Strategy

The main specification (1) used to estimate the effects of rainfall shocks on FCS is:

$$Y_{i,j,y,m} = \alpha_0 + \alpha_1 B_{i,j,y,m} + \alpha_2 Shock\_1000days_{j,y,m} + \beta X_{i,j,y,m} + \varphi R_{i,j,y,m} + \delta_j + \gamma_y + \theta_m + \mu_{i,j,y,m} \qquad (1)$$

Where the dependent variable $Y_{i,j,y,m}$ is a generic variable denoting performance in challenge tasks IC, WM, LTM or IL for child $i$ in cluster $j$, born in year $y$ and month $m$; $B_{i,j,y,m}$ is the performance of the same child in the baseline task; $Shock\_1000days_{j,y,m}$ is a variable denoting the number of rainy-season months during the first 1,000 days of life in which a rainfall shock was experienced; $X_{i,j,y,m}$ is a vector of time-invariant controls at the child/household level, $R_{i,j,y,m}$ is a vector of variables relating to the timing of the RACER tests, also defined at the child level, $\delta_j$ are cluster-level fixed effects, $\gamma_y$ and $\theta_m$ are year and month-of-birth fixed effects, respectively; and $\mu_{i,j,y,m}$ is the error term. The $\alpha_2$ term is the coefficient of interest, which denotes the impact of being exposed to extreme rainfall shocks on FCS development. Additionally, we estimate the parameter $\alpha_1$, and the vectors containing parameters $\beta$ and $\varphi$. The vector $X_{i,j,y,m}$ contains an indicator variable for the child's sex, a variable for grade of schooling completed by the parent with the higher schooling attainment, an indicator of whether the child was born prematurely, and if the house is an agricultural household. We also include an indicator variable controlling for ethnicity. The vector $R_{i,j,y,m}$ includes indicator variables taking the value 1 if the RACER test was taken on a weekend, if the test was taken between 5pm and 12am, or if the test was taken between 1 and 8am. The $\delta_j$ cluster fixed effects control for unobserved (time-invariant) characteristics common to all children in cluster $j$; and the $\gamma_y$ and $\theta_m$ year and month-of-birth fixed effects control for all common, time-specific unobserved characteristics that affect children in our sample born in the same year or month.

We will use two variations of this specification in our analysis. First, we estimate results as described, where the shock variable considers all shocks (droughts and floods) experienced during the first 1,000 days. Second, we explore whether there are key characteristics of the shocks that make them more (or less) likely to affect the development of FCS. To do this, we distinguish between abnormally high (floods) and abnormally low (droughts) rainfall shocks that happened during the pre-natal period and the post-natal period, separately.

Given that shocks are defined as monthly standard deviations from the historical means within each community, experiencing a shock during the first 1,000 days could be considered a random event, when holding the historical mean rainfall at the community-level constant. Our main identification strategy requires using three different fixed effects. First, we use community fixed effects to control for unobserved time-invariant characteristics common to all children in the community. Second, we incorporate year-of-birth fixed effects to control for yearly events that could similarly affect all children born during the same year, and finally we add a month-of-birth fixed effects to control for common effects experienced by all children born in the same calendar month.

Furthermore, our strategy significantly relies on the presence of the data for the younger siblings, as they provide much larger variation in terms of years of birth and timing of the shocks. Also, by including year-of-birth fixed effects and ages in months when the RACER tasks were taken, we are indirectly controlling for whether the child is an index child or a younger sibling. It is also important to control for age in months at which the RACER test was administered, as this may directly influence the RACER results.

Variables that control for child gender, parental schooling, mother's ethnicity, and if the child was born prematurely are included as basic controls, as they could affect results in the RACER tasks. In our data, ethnicity is approximate using the mother's language, and it consists of an indicator that takes the value of 1 if the mother's native language is Spanish, and 0 otherwise (implying it is an indigenous language). We also control for cases where the household is an agricultural household, as we expect this may be relevant in how the shock affects the results. For all of our specifications, standard errors are clustered at the district level[12].

As part of our study, we also conduct analysis to explore the different mechanisms through which rainfall could impact FCS, such as being an agricultural household, nutrition, early effects on other cognitive skills, and food security. We also include an analysis of the potential role of public policies for remediating the rainfall shock effects. A more detailed description of these additional analyses, the methodology used, and their results can be found in Section 7.

## 6. Main Results

Table 5 shows the estimates for our main specification considering the number of shocks happening during the first 1,000 days. All results have standard controls; community, year-of-birth and month-of-birth fixed effects, controls relating to the administration of the RACER application, and results for the baseline tasks, as defined in the previous section. All estimations include standard errors clustered at the district level.

Columns 1, 2, 3 and 4 report the effects of the shocks on IC, WM, IM and LTM , respectively. We find that each rainfall shock occurring during the first 1,000 days of life significantly decreases WM by 6.6% of a standard deviation. The other point estimates are statistically insignificant.

**INSERT TABLE 5 HERE**

[12] Communities (as defined in the sample) are in some cases located very close to each other (within the same district), which could lead to spatial correlation. In order to account for this possibility, we cluster the standard errors at the district level.

In Table 6, we report the estimates when distinguishing the effects of abnormally high or abnormally low shocks that happened during the pre-natal and post-natal periods. Our results confirm a negative effect of experiencing an additional rainfall shock on WM (Column 2) and IC (Column 1). While the estimated coefficients are in general larger for droughts than for floods, and during the gestational period, we are unable to reject the null hypothesis that these effects are similar. This might be due to coefficients being imprecisely estimated. No significant effects are found on IL or LTM, at any of the levels considered.

**INSERT TABLE 6 HERE**

## 7. Exploring mechanisms

### 7.1. Heterogeneous effects for agricultural households

One of the main drivers through which rainfall shocks occurring during the first 1,000 days could affect the development of cognitive skills is through the impact of shocks on agriculture. Agricultural households rely on weather for their incomes, and therefore may be vulnerable to changes and unexpected weather events that might affect their production. Thus, we investigate if rainfall shocks affect agricultural and non-agricultural households differently, based on the household main economic activity. More specifically, we estimate a fully interacted models where every control is interacted with an indicator taking the value of 1 if either the biological father or the household head works in agriculture and 0 otherwise. The parameter of interest is the interaction term between the shock variable and agricultural household indicator. The results for both the non-interacted shock variables and the interacted variables are reported in Table 7.

Our results confirm the significant negative effects of the number of rainfall shocks during the first 1,000 days on WM and, in fact, the magnitude of the effects are larger than in the main specification. In addition, we also find significant negative effects on LTM. However, we find no statistically significant differences when comparing the impact on agricultural and non-agricultural households.

**INSERT TABLE 7 HERE**

### 7.2. Effects of rainfall shocks on other earlier human-capital accumulation indicators

Since FCSs were only measured during Round 4, we need to rely on other variables to explore how rainfall shocks during early childhood could have affected the children's human-capital accumulation in earlier stages of life (i.e., before Round 4). In this sub-section, we evaluate the effects of rainfall shocks on heights-for-age at ages 5 and 8, to test if there is a nutritional channel through which the shocks might have impacted on FCS. We also evaluate the effects of shocks on receptive vocabulary test scores, observed in previous rounds of the YLS, which may allow us to find earlier effects on an important domain-specific cognitive skill.

Table 8 presents results on the impact of rainfall shocks on Height-for-Age z-scores (HAZ) at age 5 and 8, and on the PPVT score at the same ages and age 12[13]. Panel A reports the results for shocks during the first 1,000 days, while Panel B presents the results for shocks disaggregated by period and the direction of the shocks.

For HAZ, Panel A shows no effects of total rainfall shocks at any age. However, Panel B shows that there are impacts of abnormally low shocks (drought) on HAZ in childhood, both for pre-birth and post-birth shocks. Also, abnormally high shocks during the post-birth period have significant positive effects. These results suggest there might be a nutritional channel through which rainfall shocks affect FCS. It is possible that we only find these effects at age 5 because early childhood impacts on nutritional status may disappear by mid-childhood, even when FCS deficits prevail for longer.

For PPVT, Panel A shows that there are negative effects both at age 5 and age 8. The effects disappear at age 12. These results coincide with those found by Chang et al. (2022) in the case of rainfall shocks in India. This suggest that the children's cognitive skills are only affected at an early age. Similar to what we find in the case of HAZ, these results might indicate that children are capable of catching-up from the early life negative effects of rainfall shocks on domain-specific skills, such as understanding vocabulary. However, this is not the case for FCS, as we continue to detect effects at age 12, as discussed in Section 6.

**INSERT TABLE 8 HERE**

### 7.3. Effects on household's food security

In this sub-section, we explore if the rainfall shocks had an impact on the households' food security. More specifically, we measure the effect of shocks on the self-reported Household Food Insecurity Access Scale (HFIAS). We evaluate the impact of rainfall shocks that occur a year prior to the month of the interview, for each round. A limitation of this strategy is that—given the way the fieldwork was performed—most households within the same community were interviewed during the same month. This reduces the variability of the shocks, as most households within the same community experience the same number of shocks. Due to this limitation, we introduce variation between rounds, within the

[13] The information for the younger siblings comes from the rounds in which they were of similar ages.

same household. As the HFIAS questions were included in Rounds 3 and 4, we combine both rounds of answers, and control for household fixed effects. As our estimations are at the household level (the level at which these new, self-reported variables are reported), and we are including household fixed effects, we do not include child- or household-level controls.

The results are reported in Table 9. Panel A reports for the effects of the number of shocks a year prior to the interview, and Panel B divides abnormally high shocks from abnormally low shocks, for the same period. Results in Panel A show that shocks in the year prior to the interview have a positive effect on the HFIAS, implying that they increase food insecurity. This is true both for abnormally high and abnormally low shocks, as shown in Panel B. These results are consistent with the hypothesis that rainfall shocks affect households' available income to invest in children's cognitive skills through nutrition.

**INSERT TABLE 9 HERE**

### 7.4. The role of JUNTOS

In this section we test if public policies could have a role in lessening or remediating the negative effects of early rainfall shocks on FCS (see Freund et al., 2022). Indeed, Scott et al., (2022) find that receipt of Peru's JUNTOS program (the same program considered here) at a relatively younger age is associated with improvements in IC.

We estimate the impact of the shocks comparing children living in JUNTOS beneficiary households against non-beneficiaries, by estimating a fully interacted model where every independent variable is interacted by two different JUNTOS indicators: One being a dichotomic variable taking the value of one when the child was part of JUNTOS during the first 1,000 days of life, and the other being a dichotomic variable taking the value of one when the child was part of JUNTOS after the first 1,000 days of life. In the first case, the estimated parameter for interaction term would informs us if experiencing a shock while being enrolled in the JUNTOS program could have helped to reduce the effect of the shock (prevention effect).[14] In the second case, the estimated parameter gives information on the role of the conditional cash transfer (CCT) program to remediate the negative effects of rainfall shocks after the first 1,000 days (remediating effect).

[14] Scott et al., (2022) show that children receiving JUNTOS for the first time before the age of 6.7 years experienced a positive impact on Inhibitory Control, relative to those benefiting from the programme at a later age.

Table 10 shows the results for heterogeneous effects for children that are part of the JUNTOS CCT program. We only find significant effects of shocks on IC with no significant evidence of prevention due to JUNTOS, though the coefficient estimate is positive. Our estimate for a possible remediation effect of JUNTOS after the first 1,000 days for IC is significantly positive and completely offsets the negative effects of the shock. Finding that a CCT program like JUNTOS may have a remediation effect for the rainfall shocks serves as further possible evidence of the income mechanism. If rainfall is affecting FCS through household income, this may mean that cash transfers will help households increase their investments in their children and reduce the effects of the shock.

**INSERT TABLE 10 HERE**

These results, thus, provide some initial evidence of the potential for public policies to remediate the negative impact of rainfall shocks, and are consistent with literature suggesting that FCS might still be malleable at early stages of life. However, given that the JUNTOS program was not randomly allocated, but instead was focused on the "poorest among the poor", we should be careful with how we interpret these results. It could be the case that the results we observe come from the fact that these households are the poorest, and not just for being part of JUNTOS. However, in this case we should not find differences between those children that were part of JUNTOS during the first 1,000 days and those that were part of JUNTOS after the first 1,000 days, as all these children are part of this disadvantaged group.

## 8. Discussion and further analysis

This paper analyses the long-term impacts of experiencing rainfall shocks during early childhood on a set of foundational cognitive skills (FCS) including inhibitory control (IC), working memory (WM), long-term memory (LM), and implicit learning (IL). We hypothesise that these shocks can have long-lasting negative effects on cognitive development for children in vulnerable contexts, in part through affecting income via different channels. As rainfall has a major impact on agricultural production, we hypothesize that rainfall shocks that influence this activity could affect access to the resources and prices paid for inputs necessary to invest in children's FCS, not only for households that depend directly on agriculture to generate income, but also for non-agricultural households, as reduced agricultural production could affect prices and economic activity in local markets.

By matching novel data on four FCSs from the Young Lives Study with gridded rainfall data at a community level, we are able to use a fixed-effects strategy to identify the possible impacts of these shocks on these cognitive skills. Our analysis shows that rainfall shocks during the first 1,000 days of life have long-lasting negative effects on WM and IC. We also find negative effects on LTM, under certain conditions, but no evidence of effects on IL. When disaggregating the effects by type of shock and periods of the shock, for WM and IC we find that the in-utero effects are particularly important, only for this period are the point coefficients statistically significant. While point estimates are larger (in absolute values) for droughts compared to floods, statistically, the effects of both type of shocks during this period are undistinguishable.

In terms of agriculture as a possible mechanism, we do not observe any effects that are specific to agricultural households. This could be because it is not only agricultural households that are affected by these shocks, as the shocks can affect other sources of income related to agricultural output such as food prices, food availability, income sources, or access to services. However, we do observe that shocks increase self-reported food insecurity and reduce the nutritional status in childhood, which could indicate that rainfall shocks affect FCS through reductions in investment in human capital when the children are younger and, more specifically, investment in nutrition. We find evidence of early impacts of rainfall shocks on vocabulary skills, measured by the PPVT. These negative effects disappear by late childhood or early adolescent, which contrasts with the long-lasting effects on FCS found in our main analysis.

Additionally, by analysing heterogeneous effects for JUNTOS recipients, our results suggest that there may be space for public policies to remediate the negative effects of rainfall shocks on FCSs. However, we found no evidence of JUNTOS working as a preventative measure. Thus, the role of the program seems to be limited to remediating effects, possibly indicating that households are failing to optimally allocate resources over time. These results strengthen the hypothesis that the rainfall shocks affect the FCSs through decreasing households' income: That a cash transfer can decrease the negative effect of the shocks indicates that a main mechanism must be related to income.

In conclusion, our results shed light on the negative effects of early exposure to rainfall shocks on the long-term formation of children's WM and IC. Our main hypothesis states that rainfall shocks reduce agricultural output and, therefore, reduce resources and increase prices of the inputs required for investing in children's cognitive skills. Under this model, the main mechanism driving our results should be related to the rainfall shocks decreasing households' abilities to invest in children's human capital. This study provides some evidence suggesting that this might be the case.

However, our data and methodology do not allow us to directly link our results on the mechanisms to our results on FCSs. Moreover, there could be other mechanisms through which rainfall shocks affect FCSs that we have not tested in this study. Future studies should focus on understanding better the mechanisms behind the relationship between early exposure to rainfall shocks and FCS formation, as they could help to develop better prevention policies to mitigate the negative effects of these shocks in the context of climate change and poverty.

With climate change well underway, unpredictable rainfall shocks are becoming more common. These changes tend to disproportionately affect the most vulnerable households, especially those from LMICs. In contexts where inequalities are high, and many struggle to escape poverty, giving these communities the right tools to overcome more frequent weather shocks will help prevent their children from losing future human capital. Moreover, the international community must strengthen efforts to reduce global warming and, with it, the severity and persistence of these shocks.

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**Table 1. Average sample characteristics**

| | Mean | Std. Dev. |
|---|---|---|
| **Households** | | |
| Households in urban areas in Round 1 (%) | 67.57 | 46.82 |
| Household main activity is agriculture (%) | 52.61 | 49.94 |
| Mother's schooling attainment (grades) | 7.56 | 4.40 |
| Mother's primary language is Spanish | 70.40 | 45.66 |
| Regions: | | |
| Coast | 46.92 | 49.92 |
| Mountain | 34.35 | 47.50 |
| Jungle | 18.73 | 39.03 |
| Sample size | 1,511 | |
| | | |
| **Index children** | | |
| Female (%) | 49.83 | 50.01 |
| Age (years) in round 3 (2009) | 7.9157 | .2996 |
| Age (years) in round 4 (2013) | 11.915 | .30342 |
| Height-for-age (Z-score) in 2009 | -1.15 | 1.04 |
| Oldest sibling (first born) | | |
| Sample size | 1,511 | |
| | | |
| **Younger Siblings** | | |
| Female (%) | 50.41 | 50.04 |
| Age (years) in round 3 (2009) | 4.73 | 1.27 |
| Age (years) in round 4 (2013) | 8.74 | 1.28 |
| Height-for-age (Z-score) in 2006 | -1.52 | 1.51 |
| Sample size | 605 | |

**Table 2. Average foundational cognitive skills: baseline tasks and challenge tasks**

| | Baseline tasks | Challenge tasks |
|---|---|---|
| **Inhibitory control (IC)- Inverse of standardized combined average response time & accuracy** | | |
| Average | .187 | .097 |
| Index children | .210 | .121 |
| Younger siblings | .131 | .038 |
| **Working memory (WM)- Inverse of standardized average response time** | | |
| Average | -.126 | .113 |
| Index children | -.126 | .117 |
| Younger siblings | -.126 | .102 |
| **Long-term memory (LTM)- Standardized proportion of correct answers at first touch** | | |
| Average | .004 | .056 |
| Index children | .024 | .082 |
| Younger siblings | -.044 | -.007 |
| **Implicit learning (IL)- Inverse of standardized average response time** | | |
| Average | -.008 | .139 |
| Index children | -.030 | .127 |
| Younger siblings | .048 | .170 |

**Table 3: Prevalence of SPI shocks (2.0. SD) during rainy seasons**

| Period of shock | Type of shock | Average number of shocks | | |
|---|---|---|---|---|
| | | All children | Index children | Siblings |
| First 1000 days | All | 0.48 | 0.57 | 0.29 |
| | | (0.875) | (0.91) | (0.761) |
| | Abnormally high | 0.36 | 0.39 | 0.28 |
| | | (0.758) | (0.76) | (0.756) |
| | Abnormally low | 0.13 | 0.18 | 0.01 |
| | | (0.480) | (0.56) | (0.107) |
| In utero period | All | 0.18 | 0.24 | 0.06 |
| | | (0.399) | (0.44) | (0.252) |
| | Abnormally high | 0.12 | 0.15 | 0.06 |
| | | (0.331) | (0.36) | (0.248) |
| | Abnormally low | 0.06 | 0.09 | 0.00 |
| | | (0.237) | (0.28) | (0.044) |
| Post-birth (Years 1 and 2) | All shocks | 0.30 | 0.33 | 0.23 |
| | | (0.534) | (0.52) | (0.563) |
| | Abnormally high | 0.23 | 0.24 | 0.22 |
| | | (0.485) | (0.45) | (0.560) |
| | Abnormally low | 0.07 | 0.09 | 0.01 |
| | | (0.248) | (0.29) | (0.076) |

**Table 4: Prevalence of SPI shocks (2.0. SD) during rainy seasons, number of shocks**

| Period of shock | Type of shock | % of children experiencing at least one shock | | | Average number of shocks, for those experiencing at least one shock | | |
|---|---|---|---|---|---|---|---|
| | | All children | Index children | Siblings | All children | Index children | Siblings |
| First 1000 days | All | 27.0 % | 31.0 % | 16.9 % | 1.8 | 1.8 | 1.7 |
| | Abnormally high | 20.9 % | 22.9 % | 16.3 % | 1.7 | 1.7 | 1.3 |
| | Abnormally low | 6.6 % | 9.2 % | 0.6 % | 1.9 | 1.9 | 1.7 |
| In utero period | All | 17.9 % | 23.0 % | 6.1 % | 1.0 | 1.0 | 1.0 |
| | Abnormally high | 12.3 % | 15.1 % | 6.0 % | 1.0 | 1.0 | 1.0 |
| | Abnormally low | 6.0 % | 8.5 % | 0.2 % | 1.0 | 1.0 | 1.0 |
| Post-birth (Years 1 and 2) | All shocks | 27.0 % | 31.4 % | 16.9 % | 1.1 | 1.1 | 1.3 |
| | Abnormally high | 20.9 % | 22.9 % | 16.3 % | 1.1 | 1.0 | 1.3 |
| | Abnormally low | 6.6 % | 9.2 % | 0.6 % | 1.0 | 1.0 | 1.0 |

**Table 5: Main Results**

| Dependent variable: | **Inhibitory Control** | **Working Memory** | **Long Term Memory** | **Implicit Learning** |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Number of shocks during the first 1,000 days | -0.030 | -0.066*** | -0.032 | 0.025 |
| | (0.024) | (0.022) | (0.025) | (0.023) |
| Adjusted R2 | 0.371 | 0.068 | 0.482 | 0.321 |
| Number of observations | 1,714 | 1,708 | 1,705 | 1,711 |

Note: All coefficients are standardized. Controls included: community fixed effects, year and month-of-birth fixed effects, sex, the native tongue of the mother, highest education level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the house is an agricultural household, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Standard errors (reported in parentheses) are clustered at cluster level. * p<0.1 * p<0.05 ** p<0.01.

**Table 6: Main results, disaggregated between abnormally low and abnormally high rainfall shocks and between in-utero and post-birth periods**

| Dependent variable: | **Inhibitory Control** | **Working Memory** | **Long Term Memory** | **Implicit Learning** |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Number of abnormally high shocks during in-utero period | -0.104* | -0.136 | -0.173 | -0.061 |
| | (0.059) | (0.148) | (0.107) | (0.064) |
| Number of abnormally low shocks during in-utero period | -0.308* | -0.300*** | -0.222 | 0.280 |
| | (0.166) | (0.104) | (0.221) | (0.477) |
| Number of abnormally high shocks during post-birth period | 0.031 | -0.044 | 0.016 | 0.076 |
| | (0.044) | (0.088) | (0.039) | (0.061) |
| Number of abnormally low shocks during post-birth period | 0.152 | 0.250 | 0.317 | -0.226 |
| | (0.184) | (0.267) | (0.271) | (0.411) |
| Adjusted R2 | 0.372 | 0.067 | 0.483 | 0.320 |
| Number of observations | 1,714 | 1,708 | 1,705 | 1,711 |
| **F-tests (p-values)** | | | | |
| In utero low = In utero high shocks | 0.224 | 0.430 | 0.840 | 0.517 |
| Post birth low = Post birth high shocks | 0.521 | 0.372 | 0.285 | 0.503 |
| In utero low = Post birth low shocks | 0.193 | 0.146 | 0.286 | 0.576 |
| In utero high = Post birth high shocks | 0.140 | 0.689 | 0.196 | 0.266 |

Note: All coefficients are standardized. Controls included: community fixed effects, year and month-of-birth fixed effects, sex, the native tongue of the mother, highest education level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the house is an agricultural household, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Standard errors (reported in parentheses) are clustered at cluster level. * p<0.1 * p<0.05 ** p<0.01.

**Table 7: Results for agricultural households, whole sample (4 months of rainy season)**

| Dependent variable: | **Inhibitory Control** | **Working Memory** | **Long Term Memory** | **Implicit Learning** |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Number of shocks during the first 1,000 days | -0.042 | -0.105** | -0.069** | 0.015 |
| | (0.035) | (0.046) | (0.034) | (0.032) |
| Number of shocks during the first 1,000 days * Agricultural household | 0.005 | 0.040 | 0.028 | 0.002 |
| | (0.040) | (0.050) | (0.028) | (0.054) |
| Number of observations | 1,714 | 1,708 | 1,705 | 1,711 |
| Adjusted R2 | 0.377 | 0.063 | 0.495 | 0.325 |

Note: All coefficients are standardized. Controls included: community fixed effects, year and month-of-birth fixed effects, sex, the native tongue of the mother, highest education level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the house is an agricultural household, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Standard errors (reported in parentheses) are clustered at cluster level. * p<0.1 * p<0.05 ** p<0.01.

**Table 8: Effects on Height-for-age and PPVT**

| Dependent variable: | Age 5 Height for age z-score | Age 8 Height for age z-score | Age 5 PPVT | Age 8 PPVT | Age 12 PPVT |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A: First 1000 days** | | | | | |
| Number of shocks during the first 1,000 days | -0.080 | -0.002 | -1.101*** | -0.874*** | -0.188 |
| | (0.055) | (0.047) | (0.374) | (0.325) | (0.578) |
| Adjusted R2 | 0.228 | 0.276 | 0.594 | 1,662 | 1,688 |
| **Panel B: By period** | | | | | |
| Number of abnormally high shocks during in-utero period | 0.160 | 0.081 | -1.962 | 2.245 | -0.137 |
| | (0.146) | (0.137) | (1.329) | (1.772) | (0.867) |
| Number of abnormally low shocks during in-utero period | -0.206* | -0.036 | -0.154 | -2.500** | -0.166 |
| | (0.113) | (0.101) | (0.680) | (0.988) | (1.049) |
| Number of abnormally high shocks during post birth period | 0.392* | 0.064 | -0.812 | -3.175 | -6.426*** |
| | (0.230) | (0.168) | (3.830) | (5.795) | (1.448) |
| Number of abnormally low shocks during post birth period | -0.599*** | -0.130 | -3.576* | 0.535 | 5.561* |
| | (0.085) | (0.116) | (1.898) | (5.675) | (2.932) |
| Adjusted R2 | 0.229 | 0.275 | 0.593 | 0.402 | 0.367 |
| Number of observations | 1,709 | 1,712 | 1,523 | 1,662 | 1,688 |
| **F-tests (p-values)** | | | | | |
| In utero low = In utero high shocks | 0.322 | 0.944 | 0.789 | 0.415 | 0.004 |
| Post birth low = Post birth high shocks | 0.014 | 0.571 | 0.102 | 0.598 | 0.091 |
| In utero low = Post birth low shocks | 0.002 | 0.452 | 0.629 | 0.749 | 0.008 |
| In utero high = Post birth high shocks | 0.138 | 0.590 | 0.279 | 0.081 | 0.987 |

Note: All coefficients are standardized. Controls included: community fixed effects, year and month-of-birth fixed effects, sex, the native tongue of the mother, highest education level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the house is an agricultural household, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Standard errors (reported in parentheses) are clustered at cluster level. * p<0.1 * p<0.05 ** p<0.01.

**Table 9: Results on Household level food security**

| Dependent variable: | **HFIAS (R2 AND R3)** |
|---|---|
| | **(1)** |
| **Panel A: All shocks** | |
| Number of shocks (in year prior to interview) | 0.360** |
| | (0.152) |
| Adjusted R2 | 0.249 |
| **Panel B: Type of shock** | |
| Number of abnormally high shocks (in year prior to interview) | 0.429*** |
| | (0.119) |
| Number of abnormally low shocks (in year prior to interview) | 0.045*** |
| | (0.014) |
| Adjusted R2 | 0.249 |
| Number of observations | 2,656 |

Note: All coefficients are standardized. Controls included: community fixed effects, year and month-of-birth fixed effects, sex, the native tongue of the mother, highest education level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the house is an agricultural household, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Standard errors (reported in parentheses) are clustered at cluster level. * $p<0.1$ * $p<0.05$ ** $p<0.01$.

**Table 10: The role of JUNTOS**

| Dependent variable: | **Inhibitory Control** | **Working Memory** | **Long Term Memory** | **Implicit Learning** |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| **Panel B: Peru** | | | | |
| Number of shocks during the first 1,000 days | -0.071** | -0.046 | -0.041 | -0.006 |
| | (0.036) | (0.045) | (0.036) | (0.021) |
| Number of shocks during the first 1,000 days * JUNTOS during first 1,000 days | 0.078 | 0.019 | 0.025 | 0.135 |
| | (0.087) | (0.101) | (0.145) | (0.149) |
| Number of shocks during the first 1,000 days * JUNTOS after first 1,000 days | 0.081* | -0.070 | 0.003 | 0.064 |
| | (0.047) | (0.076) | (0.040) | (0.051) |
| Adjusted R2 | 0.379 | 0.071 | 0.513 | 0.326 |
| Number of observations | 1,714 | 1,708 | 1,705 | 1,711 |

Note: All coefficients are standardized. Controls included: community fixed effects, year and month-of-birth fixed effects, sex, the native tongue of the mother, highest education level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the house is an agricultural household, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Standard errors (reported in parentheses) are clustered at cluster level. * p<0.1 * p<0.05 ** p<0.01.