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Long-term effects of early life rainfall shocks on foundational cognitive skills: Evidence from Peru

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ABSTRACT

Global warming is changing precipitation patterns, particularly harming communities 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. Executive functions (EFs) are key for children's learning abilities. This paper analyses the effects of early exposure to rainfall shocks on four foundational cognitive skills (FCSs), including EFs 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 shock estimates. The key identification strategy relies on temporary climatic shocks being uncorrelated with other latent determinants of FCSs development. Our results show significant negative effects of early life exposure to rainfall shocks on EFs—especially, on working memory—measured in later childhood. We also find evidence of rainfall shocks decreasing households' abilities to invest in human capital, which may affect both FCSs and domain-specific test scores. Finally, there is suggestive, but not conclusive, evidence that a conditional-cash-transfer program providing poor households with additional financial resources might partially offset the effects of the rainfall shocks.

1. Introduction

Despite considerable progress in recent years, undernutrition among children is still highly prevalent in low- and middle-income countries (LMICs) (Black et al., 2017; Lu et al., 2016). Climate change is partially responsible for slowing down the long secular declines in undernutrition, as rapidly increasing weather variation causes more unpredictable precipitation patterns (USGCRP, 2017).[1] 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 affected by climatic shocks often experience long-term consequences for their human-capital formation, including their learning outcomes (Almond et al., 2018). The long-term implications of early life exposure to rainfall shocks on health and nutrition are fairly well-established (Skoufias and Vinha, 2012; Beuermann and Pecha, 2020; Dimitrova and Muttarak, 2020; Fitz and League, 2020; Hirvonen et al., 2020; Omiat and Shively, 2020; Randell et al., 2020). Similarly, the impact of rainfall shocks on school domain-specific achievement tests and schooling attainment have been extensively ascertained (Maccini and Yang, 2009; Thai and Falaris, 2014; Rosales-Rueda, 2018; Randell and Gray, 2019; Hyland and Russ, 2019; Chang et al., 2022).[2] However, to our knowledge, there is little population-based evidence from LMICs about the mechanisms at play, making it difficult to inform remediating policies.

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[1] In the data set used for this work, we observe that the number of shocks is increasing importantly in the years approaching 2020. This indicates that shocks, as defined in our paper, are increasingly becoming more prevalent in the context of climate change.

[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 and Sheridan, 2015).

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This paper contributes toward addressing this gap by investigating the long-term impacts of exposure to rainfall shocks, during the first 1000 days of life, on foundational cognitive skills (FCSs) in later childhood (up to 12 years of age). These skills may be important mechanisms through which climatic shocks affect domain-specific achievements and schooling attainment. There is increasing evidence on FCSs being inputs for domain-specific achievements (Lopez et al., 2024), and more specifically on executive functioning (EF) being a key domain of child development and a key predictor of educational success, including school readiness, IQ, entry level reading and math test scores (Fernald et al., 2009; Blair and Razza, 2007; Blair, 2002) and learning outcomes and scores and grade attainment during adolescence (Lopez et al., 2024). A major missing link to investigate, and the key research question of this paper, is to what extent climatic shocks have negative effects on FCSs. Weather shocks can affect cognitive skills directly and indirectly, the latter by altering investments in relevant inputs of the cognitive production function. We focus on the total effects, and specifically on the potential impact of weather shocks on the household economy (Dercon and Porter, 2014; Berhane et al., 2014; Baez et al., 2009).

We use unique data collected through the administration of a series of tablet-based tasks included in the Rapid Assessment of Cognitive and Emotional Regulation, RACER (Behrman et al., 2022; Hamoudi and Sheridan, 2015). We collected these data in 2013 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. The YL study is also the only one with data on FCSs, rarely available in large sample surveys. 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). Both inhibitory control and working memory are components of 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).

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 (Mcquade and Favara, 2024). 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 and Saunders, 2002). Then, we define rainfall shocks as those months where SPI was two standard deviations above or below the historical monthly average of the community. The focus is on rainfall during the crop-growing rainy season, as this is the period where abnormal rainfall has its largest impacts on economic activities. We consider exposure during the child's first 1000 days of life (the in-utero period, and the first two years after birth) as the event of interest given the evidence that this a sensitive period for child development (Grantham-McGregor et al., 2007; Victora et al., 2008, 2010). The YL study tracks the livelihoods of approximately 2000 children born between 2001 and 2002 (the index children). We use data from the index children as well as from their younger siblings, born between 2002 and 2007, and for whom FCS data were also collected in 2013.

We exploit rainfall fluctuations to investigate: (i) whether the exposure to climatic shocks during the first 1000 days negatively affects FCSs measured in later childhood; (ii) whether the magnitude of the impact on FCSs depends on when the shock was experienced, either during the in-utero (or 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 nutrition as one potential mechanism through which the shocks could affect FCSs. More specifically, we investigate (iii) the impact of the shocks on height-for-age and relatedly (iv) on households' food security. We then explore (v) the potential effects of rainfall shocks on vocabulary test scores, as another indicator of human-capital accumulation for which we have data from earlier in the children's lives. Finally, (vi) we explore the potential remediation role of social policies by analysing heterogeneous effects on children from families enrolled in 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 FCSs. We use district fixed effects to control for unobserved time-invariant characteristics common to all children born in various communities within the same district, alongside year- and month-of-birth fixed effects to control for the effects of common events that affect all children born during the same year or in the same calendar month.

Our results show robust negative effects of rainfall shocks on EFs, particularly on working memory. The gestational period is especially sensitive to these shocks, with abnormally low and high rainfall both reducing working memory and inhibitory control. Furthermore, our results provide some evidence on the reduction of households' incomes as a potential mechanism through which rainfall shocks affect FCSs. Specifically, rainfall shocks seem to affect households' investment in their children's nutrition. We also find evidence of the same shocks affecting performance in vocabulary test scores at age 5, prior to the ages FCSs were measured in YLS. Since there is evidence of FCSs being predictors of domain-specific scores and educational outcomes later in life (Lopez et al., 2024), this suggests that the effects on FCSs were felt earlier than observed in our data. Finally, we find suggestive evidence that public policies aimed at providing financial support to poorer families might partially remediate for the negative effects of rainfall shocks on FCSs.

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, as well as the impact of these shocks on FCSs and their importance for future outcomes; Section 3 outlines the conceptual framework; Section 4 and Section 5 describe, respectively, the data and the empirical strategy; Section 6 presents the main results; Section 7 investigates other results such as potential mechanisms behind the relationships uncovered between rainfall shocks and FCSs; Section 8 concludes.

2. Literature review

2.1. The impact of rainfall shocks on education attainments and cognitive skills

The long-term implications of early life exposure to rainfall shocks on educational attainments are fairly well-established, although the evidence might seem quite mixed as it reflects the different contexts and channels through which climatic shocks may affect human-capital accumulation. Furthermore, some studies only find effects for women (Maccini and Yang, 2009) and others find effects only on rural households (Hyland and Russ, 2019). The type of shocks (abundant or scarce rainfall) and the timing of shocks (for example whether the shock occurs in the agricultural season) also seems to matter (Fitz and League, 2020).

There is an existing literature suggesting that abundant rainfall positively affects educational outcomes mainly through a positive impact on agricultural output, as argued, for example by Maccini and Yang (2009). They find that higher rainfall (measured as total deviations from mean log rainfall) during the year of birth in Indonesia (but not after or prior to birth years) leads to higher schooling attainment (for women exclusively). Similarly, Thai and Falaris (2014) find that higher rainfall during the year of birth and the third year of life in Vietnam, shortens school-entry delays and enables faster progression through school. Randell and Gray (2016) find that an increase in rainfall during the summer agricultural season in rural Ethiopia is associated with increased probabilities 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. Importantly, this part of the literature does not focus on extreme events (such as droughts or floods), but only on rainfall variation.

Focusing on rainfall shocks, Hyland and Russ (2019) use DHS data for women in 19 countries in sub-Saharan Africa and find that being exposed to droughts (measured as dichotomic variables taking a value of one when deviations are below a certain threshold) during early childhood has negative effects on schooling attainment, adult heights and wealth (for women from rural households only). Similarly, Randell and Gray (2019) use census data for 29 countries in the Global South and 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 more schooling attainment for children in Central America and the Caribbean).

Some papers argue 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. For example, Shah and Steinberg (2017) find that, for children aged 5–16, droughts in India affect children's educational attainment positively, as—they argue—they push children away from agricultural work. Other studies note that there is a nutrition-learning link that is triggered by climatic 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.

While the evidence of rainfall shocks on schooling attainment is quite abundant, evidence on the impact of climatic shock on learning outcomes is less common, and often focused on domain-specific achievement tests. Rosales-Rueda (2018) exploits the *El Niño* phenomenon in Ecuador to show evidence of negative effects of early life exposure to excessive rainfall (floods) on the Peabody Picture Vocabulary Test (PPVT). Similarly, Aguilar and Vicarelli (2022) use data from Mexico to find that rainfall shocks during the *El Niño* phenomenon have negative effects on PPVT. Notably, this study also finds negative impacts of *El Niño* on long-term and working memory, and visual-spatial thinking. They find that these effects are larger on children affected during their first and second year of life. Finally, Chang et al. (2022) use the YLS data to evaluate the long-term effects of in-utero rainfall shocks on domain-specific achievement tests in India. They find negative long-lasting effects on math-test scores at age 15, but only short-term effects on the PPVT.

To the best of our knowledge, there is limited evidence on the impact of rainfall shocks on FCSs, or domain-general cognitive skills, despite the increasing evidence of FCSs, and more specifically EF, being an input for domain-specific achievement tests and a key predictor of educational success (Behrman et al., 2022; Fernald et al., 2009; Blair and Razza, 2007; Blair, 2002; Lopez et al., 2024). This is likely due to a lack of suitable data.[3] Besides Aguilar and Vicarelli (2022), another exception is Freund et al. (2024).

Interestingly, EFs are 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 EFs are 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 and Garner, 2012; Nelson and Sheridan, 2011; McLaughlin et al., 2014; Sheridan and 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.

[3] Many of the existing studies on EFs or, more generally, FCSs, 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 at risk (Black et al., 2017; Lu et al., 2016). Furthermore, most evidence comes from experimental studies, with often (very) small samples.

2.2. How climatic shocks affect cognitive skills

There are multiple channels through which climatic shocks may affect human-capital accumulation. The existing literature suggests that climatic shocks may affect cognitive skills predominantly 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, such as nutrition). Most evidence on the direct effects comes from the medical literature,[4] while evidence on indirect effects comes predominantly from the economics literature (Dercon and 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 prior evidence.

A key 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 and the consumption of non-agricultural households (Dercon, 2004; Jayachandran, 2006; Amare et al., 2018). However, non-agricultural households could also be impacted (Rijkers and Söderbom, 2013; Grabrucker and 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 low or high rainfall levels could affect other sources of income either directly linked to agriculture and food prices (wholesale and retail trade, transportation, 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 and Muttarak, 2020; Omiat and Shively, 2020; Bauer and Mburu, 2017; Cornwell and Inder, 2015; Skoufias and Vinha, 2012). The existing evidence suggests that poor nutritional status is associated with lower FCSs, and particularly with lower EFs (Sánchez et al., 2024). These impacts are particularly relevant during the first 1000 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 literatures (Victora et al., 2008, 2010; Maluccio et al., 2009; Almond et al., 2018).

3. Conceptual framework

Following closely Todd and Wolpin (2003), and Glewwe and Miguel (2007), we consider a framework in which the first 1000 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 $t=1$, the family of child i can invest in cognitive skills ($S_{i,1}$), as follows:

$$S_{i,1} = f_1(F^S_{i,1}, F^H_{i,1}, S_{i,0}) \tag{1}$$

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

$$S_{i,2} = f_2(F^S_{i,2}, F^H_{i,2}, S_{i,1}) \tag{2}$$

Here, $F^S_{i,2}$ and $F^H_{i,2}$ represent investments in period 2. For simplicity of

[4] 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)

exposition, we assume parents are altruistic with regard to their children, so that they gain utility from their children's cognitive skills in addition to their own consumption.[5] The utility function for family i can be expressed for the one-child case as:

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

where $C_{i,t}$ 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 ($I_{i,t}$) with, again for simplicity, no transfer of budgetary resources across periods. We assume household income is negatively correlated with rainfall shocks (θ), and the prices of inputs p are positively correlated with these shocks, under the usual assumption that markets in LMICs tend to be segmented and only weakly linked to national and international markets.

$$I(\theta)_{i,t} = p(\theta)^c_t C_{i,t} + p(\theta)^H_t F^S_{i,t} + p(\theta)^S_t F^H_{i,t} \tag{4}$$

Within this framework, parents are expected to choose optimally for inputs $F^S_{i,t}, F^H_{i,t}$, and consumption $C_{i,t}$ 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 Eq. 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 relying on agriculture as the primary source of income and/or consumption, include finding other sources of income outside of the agricultural sector, or investing more time working on the farm. These other strategies could still result in decreases in inputs for cognitive skills, as they could force caregivers into the labour market and away from child care 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, $F^S_{i,1}$ or $F^H_{i,1}$.

All of these strategies have the peculiarity that, even if they help mitigate the negative effects of the shock by increasing income $I(\theta)_{i,t}$, they do nothing to reduce the size of the impact θ, which might still affect prices and consumption, and, therefore, still affect household investments in children's cognitive skills.

An important characteristic of our model is that the effect of shocks in period 1 is expected to be persistent, as the production function of cognitive skills in period 2 ($S_{i,2}$) depends on skills acquired on the previous period $S_{i,1}$ (self-productivity) that depends on shocks in period 1. Remediation is theoretically possible through additional investments in period 2, although the persistency of the effect would require these investments to be higher than if the shocks are fully mitigated in period 1.

[5] 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.

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 2015/2016 (Round 5). For the empirical analysis, we use a sample of 1207 children (index children) who were born in Peru in 2001–2002 and were aged between 6 and 18 months in the first survey round. In addition, we use information on a sample of 521 younger siblings born in 2002–2007, aged 2–8 years in 2009/10 (Round 3), the first time they were interviewed.

In all rounds, a child questionnaire, including data on child health, anthropometrics and education, and a household questionnaire, including questions on caregiver background, livelihood, household composition, socio-economic status, shock was administered. In addition, test scores in vocabulary and mathematics were collected since Round 2 (2006/07).

The index children were initially enrolled in 2002 from 82 communities, within 20 selected districts (the smallest geopolitical sub-division in Peru), 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 ages 6–18 months. 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 procedure was followed until the desired sample size was met. The final sample of YLS index children represents the poorest 95 % of children from both urban and rural areas in the three main geographical regions: coast, highland (altiplano) and jungle. More information on the sampling strategy can be found in Escobal et al. (2003).

The data on younger siblings were collected since Round 3, from every household in the study for which the index children had a younger sibling at the time. Only the younger sibling closest in age was considered. Since then, information on the younger siblings has been collected in every following round, including key characteristics, such as anthropometrics and test scores. Sibling children were born between 2002 and 2007, with more than half born between 2003 and 2004. The inclusion of the younger siblings is a fundamental part of this study, as it allows to increase within-cluster variability in weather conditions during the first 1000 days.

Although the YLS samples are not nationally representative, comparisons with Demographic Health Survey (DHS) data show that the index group covers the diversity of children in Peru (Escobal and 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 used in this paper is 6.3 %, which is 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 and Escobal, 2020).

4.2. Measurements of FCSs

Data on FCSs were collected during Round 4 (2013). At that time, the index children were aged 11–12 years, whereas the younger siblings were aged 5–11. The FCSs were measured using a series of computer-based tasks through Rapid Assessment of Cognitive and Emotional Regulation (RACER) (Hamoudi and Sheridan, 2015; Ford et al., 2019; Behrman et al., 2022). RACER is a novel touch-screen computer/tablet application that uses five short tasks (one to four minutes each) to assess four components of FCSs (Inhibitory Control- IC, Working Memory- WM, Long-term Memory- LTM, and Implicit Learning- IL) in children aged 6

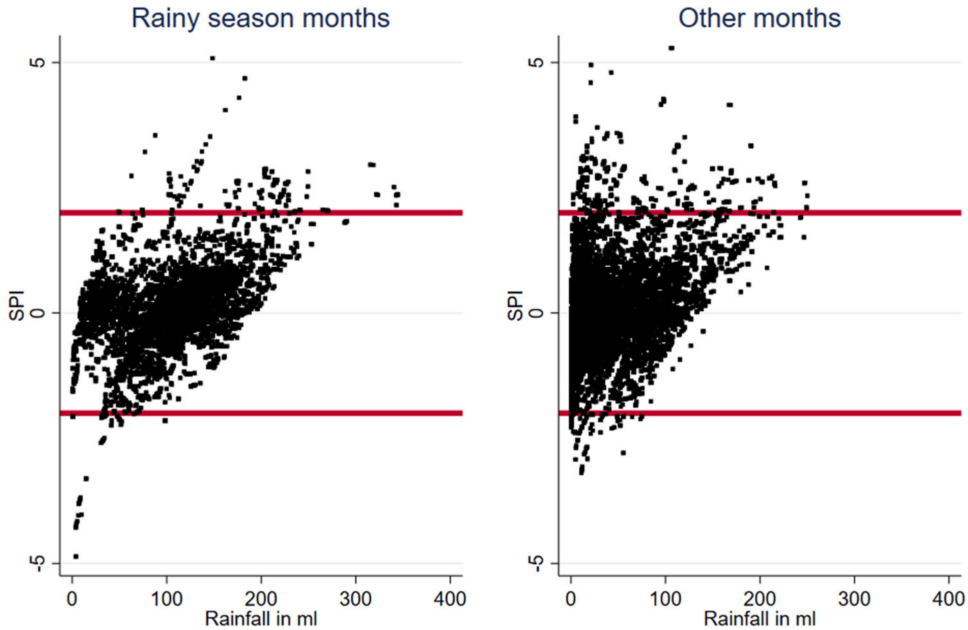

Fig. 1. Average rainfall in millilitres and SPI, for each community and month in the sample. (1996–2010). Note: Observations correspond to data observed for each community, in each month and year (1996–2010), regarding the level of SPI (y-axis) and rainfall quantity measured in millilitres (x-axis). Red lines represent 2 and −2 SPI.

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 and 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).

For both the challenge tasks and the baseline tasks, LTM is measured by the proportion of correct answers, IL and WM by response times, and IC by a linear combination of response time and accuracy (equally weighted). Children who perform better in LTM 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 IC would provide more spatially accurate responses. 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.[6] More information about RACER and the FCSs measured in the YLS can be found in Hamoudi and Sheridan (2015) and Behrman et al. (2022).

4.3. Rainfall data

Rainfall data are obtained from the University of Delaware, a commonly used climatic dataset (see, for instance, Shah and Steinberg 2017; Rocha and Soares 2015; and Thai and Falaris 2014). These data contain gridded estimates of monthly total precipitation across land surfaces between 1900 and 2017 (Matsuura and Willmott, 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 YLS communities in Peru.[7] 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 and Favara, 2024).[8] 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.

As per the definition of rainfall shocks adopted in this paper, there are three important aspects that are worth emphasizing. First, we use the Standard Precipitation Index (SPI) as opposed to the direct rainfall data (Lloyd-Hughes and Saunders, 2002). We can define the SPI as the standard deviations of total rainfall compared to the long-term local average, if rainfall was measured as a normally distributed random variable.[9] Second, we focus on shocks happening during the rainy-season months. Third, we define as rainfall shock any monthly-community-specific rainfall above or below 2 standard deviations from the historical mean of a given community in a given month. In what follows we justify these

[6] For standardization, we use the combined sample of all children in Ethiopia (the other YLS country in which RACER was applied) and Peru.

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

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

[9] SPI compares the cumulative precipitation over a defined period of time in a specific geographical area to its cumulative average. The construction of the SPI in this study follows McKee et al. (1993). We calculated the average monthly rainfall in each community for the period of 50 years. Since rainfall has a skewed distribution, with high prevalences of low values and a decreasing probability of finding larger values and will not take negative values, McKee (1993) proposes an incomplete Gamma distribution as the closest universal representation of rainfall probability. We fitted this probability density function to the frequency distribution of precipitation summed over 50 years, which transforms the distribution into a standardised normal. This was performed for each month and each community, separately. More information on how this variable was constructed can be found in McQuade and Favara (2024).

methodological choices.

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 at zero millilitres of rain and exhibit a skewed distribution. The SPI *normalises* the data, making both positive and negative shocks equally represented, allowing for a better representation of droughts in the data. We calculate the SPI for every community using data from the last 50 years.

In relation to our focus on the rainy-season months, as discussed earlier, a potential channel through which climatic shocks could affect FCSs is through impacts on agricultural outputs, which, in turn, may have impacts on both agricultural and non-agricultural households. Small variations in rainfall might not be relevant for dry months where the expected rainfall is close to zero. 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. Similar to Fitz and League (2020), we defined rainy-season months as the 4 months with the highest average monthly rainfall in each community.[10] Additionally, we explored the robustness of our results to a 6-month rainy season definition in Section 6.2.

Fig. 1 shows the distribution of the SPI level versus total rainfall in millilitres for each month and community in the sample between 1996 and 2010 (each dot representing a month and community pair), for both rainy season and non-rainy season months. The two horizontal lines correspond to the 2 standard deviation thresholds used to identify rainfall shocks. As observed, the non-rainy season months include many SPI shocks that imply a negligent amount of rainfall. Thus, by limiting the definition of shocks to consider only those occurring during the rainy season months, we effectively exclude positive SPI shocks that are equivalent to almost zero millilitres of rainfall.[11] In other words, it allows us to focus on the shocks that not only represent high deviations from the month's average, but that do so in the periods where they imply higher variations in total rainfall, which also are key months for agricultural production.[12]

4.4. *Defining rainfall shocks in the in-utero and early childhood periods*

We initially define a shock as any monthly SPI deviation of at least 2 standard deviations below (*abnormally low rainfall shocks*) or above (*abnormally high rainfall shocks*) the historical monthly average for the same community during each rainy-season month. The use of the 2 standard deviation thresholds is consistent with the fact that SPI resembles a normal distribution, allowing us to capture extreme dry and wet events (Mcquade and Favara, 2024) — later we discuss the sensitivity of the results to changing the selected thresholds. To assess the role of early-life shocks, we focus our attention on the intensive margin, i.e., the number of shocks occurred during the first 1000 days, critical for human-capital development.

Information about the date (and place of birth) of each YLS child is used to define the period of interest, and to distinguish between rainfall shocks that occurred during the in-utero period and shocks that occurred during the early childhood period (the first and second years after birth).[13] 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.

The date of conception and the gestational period of each YLS child is defined assuming 38 weeks (266 days) as an approximation of a normal-term pregnancy, as per the World Health Organization definition.[14] Under these assumptions, the index children in our sample were conceived between March 2000 and October 2001, while the younger siblings were conceived between September 2002 and March 2007. We account for premature births (about 25 % of the children in our sample) by including as a control an indicator capturing whether a child was born prematurely, based on information self-reported by the children's mothers.

4.5. *Sample definition*

As explained, this study uses a subsample of the Peruvian YLS sample containing RACER data. This original dataset has a total of 2641 observations, between index children and their siblings, spread over 82 communities. To impute accurately exposure to rainfall shocks during the first 1000 days, given the available data, we restrict the sample to households that had not moved from the community where the index child was born up until Round 3 (2009), which accounts for 79 % of the original sample.[15] We discuss potential issues of sample selectivity in Section 6.2. The final subsample of non-migrant families includes a total of 2121 children. Because of unavailability of weather data,[16] the

[10] Rainfall shocks happening during the rainy season also work as a proxy for the period in which most crop-choice decisions should have already been made. This is an important consideration, as farmers could potentially mitigate effects of rainfall shocks by shifting their production to more resilient products (either more water-resistant or less water-dependent) during a given crop year if the rainfall shock arrives before the beginning of production. Here 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 and pesticides. For agricultural households, these decisions imply a reallocation of household resources to buy such inputs, which could in turn still affect the amount resources devoted to children's development.

[11] The way the SPI is defined might impose larger values to months with almost no rainfall for certain communities. In the case of the Peruvian sample, this is due to certain locations naturally experiencing dry seasons during certain months, particularly on the coast. As such, any small increase in rainfall during a dry-season month can potentially induce larger values of SPI.

[12] We attempted using an alternative specification that considered all months, which led to unclear results. This should not be surprising, as it is unclear what effect should be expected from shocks in all months, when some of these shocks are minimal changes in rainfall.

[13] We decided to consider the intensity of the shocks by measuring the total number of months in which shocks were experienced during rainy seasons, as the impact of multiple rainfall shocks should be harder to prevent or mitigate. Earlier versions of this document included results for a dichotomic variable taking the value of one if the child experienced at least one shock and zero otherwise, which lead to results comparable to those in the present document.

[14] 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.

[15] 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. 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. 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 prior to Round 3. This allows us to define the community of residence during the relevant periods.

[16] Weather data were not available for all communities because not all communities had GPS information. The main reason for this lack of data is that GPS information was not collected until round 2, which implies that some of the communities in round 1 might have changed names, been split, or ceased to exist. Additionally. More information regarding the generation of the weather data can be found in McQuade & Favara (2024).

Table 1
Average sample characteristics.

	Mean	Std. Dev.
Households		
Households in urban areas in Round 1 (%)	60.4	48.9
Household main activity is agriculture (%)	64.4	47.9
Mother's schooling attainment (grades)	7.0	4.47
Mother's primary language is Spanish (%)	66.1	47.4
Regions:		
Coast (%)	40.2	49.0
Mountain (%)	36.9	48.3
Jungle (%)	22.8	41.9
Sample size	*1212*	
Children		
Female (%)	50.5	50.0
Height-for-age (Z-score) in 2009	-1.23	1.05
Age (years) in round 4 (2013) – Index Children	12.5	.5
Age (years) in round 4 (2013) – Younger Siblings	9.36	1.3
Sample size	*1728*	

sample is reduced to 1728 children, with 1207 index children and 521 younger siblings.[17] The final sample covers 72 communities, distributed across all three climatic regions of Peru (coast, highland, and jungle). Table 1 presents some descriptive statistics of this sample.

It is worth mentioning that, even though three fifths of our Peruvian households are defined as urban households, 35 % of these urban households report agriculture as their main economic activity. In the Peruvian context, it is common for agricultural workers to live in urban areas and work in agricultural land in the outskirts of the urban center, or even by having family members seasonally relocating to rural areas.

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

Table 2 reports the average number of shocks experienced by the children in our sample, the percentages of children who experience at least one shock and the SPI standard deviation. On average children experience less than half a shock during their first 1000 days of life, implying that many children did not experience any shocks during this period. In total, 27 % of children experience at least one shock during the first 1000 days of life, with a higher prevalence (27 %) during the first two years of life compared to the in-utero period (17 %). 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. Table 2 also presents information about the prevalence of abnormally high and abnormally low rainfall shocks, with the former being more prevalent than the latter.

5. Empirical strategy

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

$$Y_{i,j,y,m} = \alpha_0 + \alpha_1 B_i + \alpha_2 Shock\_1000days_{j,y,m} + \beta X_{i,j} + \varphi R_i + \delta_j + \gamma_y + \gamma_m + \mu_{i,j,y,m} \quad (5)$$

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 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 1000 days of life in which a rainfall shock was experienced for someone born in cluster j, born in year y and month m[18]; $X_{i,j}$ is a vector of time-invariant controls at the child/household level, R_i is a vector of variables relating to the timing of the RACER tests, also defined at the child level, δ_j are cluster-level fixed effects,[19] γ_y and γ_m are respectively year and month-of-birth fixed effects; and $\mu_{i,j,y,m}$ is the error term that for all of our specifications is clustered at the district level.[20]

We use two variations of this specification in our analysis. First, we estimate results as described, where the shock variable considers any type of shocks (both abnormally low and abnormally high rainfall shocks) experienced during the first 1000 days. Second, we distinguish between abnormally low and abnormally high rainfall shocks that happened during the in-utero period and the post-natal period.

The α_2 term is the coefficient of interest, which denotes the impact of being exposed to an additional rainfall shock on child's FCSs. Conditional on our selected controls, our estimate of α_2 takes on a causal interpretation under the assumption that the probability of experiencing a rainfall shock in the first 1000 days is uncorrelated with other latent determinants of FCSs.

Given that shocks are defined as monthly standard deviations from the historical means within each community, experiencing a shock during the first 1000 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 district fixed effects to control for unobserved time-invariant characteristics common to all children in the same district. Second, we incorporate year-of-birth fixed effects and month-of-birth fixed effects to control for all time-specific unobserved characteristics that might be common and affect equally children born in the same year or month.

A wide set of controls is included to improve the precision of our estimates, as there could be heterogeneity in FCS results in many of these dimensions (Behrman et al., 2022). We included the performance at the baseline task B_i to control for other unobserved differences that might have affected the performance in RACER tasks (for example the child's general abilities to follow instructions or answer computerized tasks) and are not necessarily indicative of difference in FCSs. The vector $X_{i,j}$ contains an indicator variable for the child's sex, a variable for grade of schooling completed by the parent with the highest schooling attainment, mother's ethnic tongue (as a proxy for child's ethnicity),[21] an indicator of whether the child was born prematurely, and if the household is agricultural (as we expect this may be relevant in how the shock affects the results). The vector $R_{i,j,y,m}$ includes three indicator variables taking the values 1 if the RACER test was taken on a weekend, if the test was taken between 5 pm and 12 am, or if the test was taken between 12 am and 9 am.

[17] We also observe differences in the number of observations for each independent FCS, as not all tasks were completed by all children that participated of RACER. This led to a total of 1714, 1708, 1705 and 1711 observations for Inhibitory Control, Workimg Memory, Long-Term Memory and Implicit Learning, respectively.

[18] The main specification of this study does not distinguish between abnormally low or abnormally high shocks, under the assumption that both a shortage and an excess 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 abnormally low and abnormally high rainfall shocks.

[19] Communities (as defined in the sample) are in most cases located very close to each other (within the same district), for which reason we observe very little variability in rainfall between communities in the same district. Most communities are also small in terms of number of observations, for which reason we do not have enough variation in ages within each community. Therefore we use district-level fixed effects.

[20] This was done to account for spatial correlation.

[21] In our data, ethnicity is approximated 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).

Table 2
Prevalence of SPI shocks (±2 SD from means) during rainy seasons, number of shocks.

Period of shock	Type of shock	Average number of shocks (in months)	Standard deviation	Max	% of children experiencing at least one shock	Average number of shocks (in months), for those experiencing at least one shock
First 1000 days	All	0.48	0.875	5	27.0 %	1.8
	Abnormally low	0.13	0.480	2	6.6 %	1.9
	Abnormally high	0.36	0.758	5	20.9 %	1.7
In-utero period	All	0.18	0.399	2	17.9 %	1.0
	Abnormally low	0.06	0.237	1	6.0 %	1.0
	Abnormally high	0.12	0.331	2	12.3 %	1.0
Post-birth (Years 1 and 2)	All shocks	0.30	0.534	4	27.0 %	1.1
	Abnormally low	0.07	0.248	1	6.6 %	1.0
	Abnormally high	0.23	0.485	4	20.9 %	1.1

Table 3
Main results.

Dependent variable:	Inhibitory Control (1)	Working Memory (2)	Long-Term Memory (3)	Implicit Learning (4)
Number of shocks during the first 1000 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	1714	1708	1705	1711

Note: Controls include: district fixed effects, year and month-of-birth fixed effects, child's sex, mother's native tongue, highest schooling level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Index children and siblings included. Standard errors (reported in parentheses) are clustered at district level. * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

Furthermore, our strategy significantly relies on the presence of 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. As an alternative specification, we conducted an analysis replacing the district fixed effects by household fixed effects. This approach has the advantage of controlling for time-invariant characteristics at the household level that might affect parental investments in human capital as well as their ability to respond to shocks. However, this approach has two main shortcomings: first, the sample size declines; second, it reduces much of the variations we have in the data in relation to the timing of the shocks. As a result, although the household fixed-effects model leads to results qualitatively equivalent and similar in magnitude, the statistical significance of the estimated parameters declines.

6. Main results

6.1. Effects of rainfall shocks on FCS

Table 3 shows the estimates for our main specification considering the number of shocks occurring during the first 1000 days. All results have standard controls listed in the table note and defined in the previous section. All estimations include standard errors clustered at the district level.

Columns 1–4 report the effects of the shocks on IC, WM, LTM and IM, respectively. We find that one additional rainfall shock occurring during the first 1000 days of life significantly decreases WM by 6.6 % of a standard deviation.[22] The other point estimates are statistically insignificant. These results are qualitatively similar when using alternative definitions of rainfall shocks, e.g. considering 1.5 standard deviations as a threshold defining shocks, as we will show in Section 6.2.

Table A1 in the Appendix shows the same table, with additional specifications. Columns 1, 5, 9, and 13 exclude all controls except RACER related controls,[23] for IC, WM, LTM and IL, respectively. Columns 2, 6, 10 and 14 include standard controls at the household level and month- and year-of-birth fixed effects. Columns 3, 7, 11 and 15 show the same estimates as those in Table 3; that is, including also district-level fixed effects. Finally, columns 4, 8, 12, and 15 exchange district-level fixed effects for household-level fixed effects.

These results show that our conclusions on WM are robust to excluding various controls. Additionally, we find statistically significant negative effects on inhibitory control and implicit learning before introducing the district fixed effects. However, they become small once we include district-level fixed effects, losing their statistical significance. None of our results using household-level fixed effects remain significant. This can be attributed to a reduction in the sample size due to the exclusion of households where index children have no siblings, as well as a reduction in the variation.[24] In fact, we observe a higher coefficient for the effects on WM, as well as higher standard errors.

In Table 4, we report the estimates when distinguishing the effects of abnormally low or abnormally high shocks that happened during the in-utero and post-natal periods. Our results confirm a negative effect of experiencing an additional rainfall shock on WM (column 2) and in addition we find a negative impact on IC (column 1) too. While the estimated coefficients are in general larger for abnormally low than for abnormally high rainfall shocks, and during the gestational period, we

[22] This is similar to the standardized coefficient as the standard deviation of number of shocks distribution is 0.88, as reported in Table 2.

[23] The inclusion of baseline trial controls allows us to clean out the effects of rainfall shocks through other skills that are not FCSs. Although this is an important part of our estimation, it also could make our results an underestimate of the effects of the rainfall shocks on cognitive skills. In an additional specification not reported in this document, we tested for the robustness of our results to the exclusion of these baseline trials. This exercise led to almost identical results to those in our main analysis, implying that even if some downward bias induced by the introduction of the baseline trials could theoretically exist, in our data this must be too small to be relevant.

[24] The sample does not only decrease, but we are also left with only 45 % of households experiencing shocks, and only 10 % are siblings experiencing shocks in households where the index children did not experience a shock, while the other 20 % of siblings experiencing shocks are in households where the index children also experienced a shock.

Table 4
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 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 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 post-birth period	0.152	0.250	0.317	-0.226
	(0.184)	(0.267)	(0.271)	(0.411)
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)
Adjusted R2	0.372	0.067	0.483	0.321
Number of observations	1714	1708	1705	1711
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: Controls include: district fixed effects, year and month-of-birth fixed effects, sex, mother's native tongue, highest education level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Index children and siblings included. Standard errors (reported in parentheses) are clustered at district level. * p<0.1 ** p<0.05 *** p<0.01.

are unable to reject the null hypothesis that these effects are similar. This might be due to coefficients being imprecisely estimated We corrected for multiple hypothesis testing following Anderson (2008). When doing so, the resulting sharpened q-values for our results on Inhibitory Control fall below the 10 % significance level, but our results on WM remain significant. No significant effects are found on IL or LTM.

6.2. Robustness

In this section, we conducted a number of robustness checks to test whether our results hold when adopting different definitions and specifications.

First of all, we tested the robustness of our results when changing the definition of rainy season from being 4 months to being 6 months long, in order to include potentially longer rainy seasons in communities located in the jungle. As shown in Panel A of Table A2, the results under this alternative definition are comparable, both in magnitude and in significance, to the main results obtained under the 4 months- rainy season definition.

Second, we tested the robustness of the main results when adopting a lower SPI threshold to include not just *extreme events* (i.e. SPI above the absolute value 2 threshold) but also *severe shocks* (i.e. any shock above the absolute value 1.5 threshold, as defined by McKee et al., 1993). As in our main specification, we find significant results on WM that are comparable in sign and size to our main specification (see Panel B, Table A2).

Third, we are interested in testing to what extent our definition of rainfall shocks was capable of predicting extreme rainfall events as perceived by the households. For this exercise, we used the data collected in round 2 and 3 on the households' self-reported perceived floods and droughts. Table A3 shows that abnormally low shocks are typically associated with self-reports of droughts and increase the probability of reporting a drought by 13 %. Abnormally high shocks do not seem to necessarily lead to a higher perceived probability of flood. As an additional exercise, we divided the sample according to natural regions (coast, highland and jungle) to test for differences in the effects of rainfall shocks on perception of floods and droughts. We found that our definition of shock was particularly predictive of perceived disasters for households located in the highland region, where positive shocks decreased the probability of perceiving droughts (17 %) and increased the probability of perceiving floods (2 %), while negative shocks increased the probability of perceiving droughts (13 %).

Fourth, we test for the robustness of our results to excluding households located in the jungle region of Peru. As discussed in Section 4.2, there are important differences in the total annual rainfall experienced in the different localities across the three Peruvian climatic regions- jungle, coast and highland-with the first receiving a significant higher amount of rain compared to the other two. When excluding respondents residing in the jungle, we still find significant negative impacts on WM, although larger in size (see Table A4 in the Appendix).

Finally, we investigate whether our main results might be biased due to migration. Our main specification focuses on a subsample of children for whom we could confidently identify their or their mothers' places of residence in each relevant period. That is, we excluded children whose mothers migrated during the gestational period, i.e. those who moved to the Round 1 community after birth (or to give birth); or that lived in the Round 1 location for less than 9 months. We also excluded children that migrated prior to Round 3. This was done to reduce measurement error, either by wrongly imputing shocks to children that did not experience them, or by assuming children were not exposed to shocks when they were. However, excluding the migrants could introduce bias. For example, it could be that households affected by shocks during Round 1 were so severely affected that they decided to migrate before Round 3. This would lead to downward estimates of the impact of the rainfall shock. Similarly, it could be that only the wealthiest households, presumably less vulnerable to rainfall shocks, were able to migrate after experiencing the shocks. This would have had the opposite bias, as we would be left only with those most affected by the shocks. To account for this problem, we adjust our estimation sample to include the migrants. Results shown in Table A5 in the Annex are similar to estimates from our main specification, although relatively smaller in magnitude.

7. Exploring mechanisms and remediation policies

In this section we explore some other results that can help understand the impact of rainfall shocks on FCSs. Our findings presented so far suggest that being exposed to rainfall shocks early in life has negative impacts on at least some aspects of FCSs later in childhood. However, this effect might have showed up earlier in life. As no earlier measures of FCSs are available, in Section 7.1 we investigate the impact of the rainfall shocks on other indicators of human-capital development, including nutrition (proxied by heights-for-age at ages 5 and 8) and domain-specific achievement (using the Peabody Picture Vocabulary Test (PPVT) at age 5, 8 and 12. These results can be interpreted as evidence of potential mechanisms—i.e., as proxies for earlier investments in nutrition and cognitive skills—driving the latter results on FCS. In Section 7.2 we further explore the negative impact of rainfall shocks on nutrition by investigating to what extent they affect households' food security. Then, in Section 7.3 we explore the potential remediation role of a conditional cash transfer program (JUNTOS).

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

Table 5 presents results on the impact of rainfall shocks on Height-for-Age z-scores (HAZ) at approximately ages 5 and 8, and on the PPVT score at the same ages and at age 12.[25] Panel A reports the results for shocks during the first 1000 days, while Panel B presents the results for shocks disaggregated by period and the direction of the shocks.

Panel A shows that an increase in the number of shocks has no clear effect on HAZ. However, when disaggregating the shocks by timing and type of shocks (Panel B) we find that an increase in the number of abnormally low shocks has a significant impact 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 (at 10 % level). None of our results associated with p-values below 10 % significance level remain significant when correcting for multiple hypothesis testing. These results suggest there might be a nutritional channel through which rainfall shocks affect FCSs. 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 FCSs deficits prevail for longer.

For PPVT, Panel A shows that there are negative effects both at age 5 and age 8. The overall effects disappear at age 12. These results coincide with those found by Chang et al. (2022) in the case of rainfall shocks in India, and suggest that the children's domain-specific 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, following early life negative effects of rainfall shocks on domain-specific skills, such as understanding vocabulary. Notably however, disaggregating the shocks in Panel B suggests a significant impact on PPVT may still exist (even at age 12) following positive rainfall shocks during childhood. The impact of these shocks appears to be attenuated in the overall effect by a positive effect relating to low rainfall during the same period. In the case of FCSs however, we clearly continue to detect effects at age 12, as discussed in Section 6. Interestingly, the effects detected on FCS came from shocks during the in-utero period, while shocks during the post-birth period seem to be more relevant for PPVT. This might be revealing of the differences in nature of the skills measured.

It should be noted that results of shocks on PPVT can be interpreted both as evidence that shocks alter early investments in human capital as an earlier measurement for cognitive skills – in which case it would be correlated with an unobserved earlier measurement of FCS –, and therefore it also could be interpreted as a proxy for the mechanism leading to future FCS development. That is because rainfall shocks can affect PPVT directly or through effects on FCS, while domain specific skills such as those measured by the PPVT (vocabulary) can be affected by previous FCS and affect future FCS development.

Table 5
Effects on Height-for-Age z scores and PPVT.

Dependent variable:	Age 5 Height for Age z-score (1)	Age 8 Height for Age z-score (2)	Age 5 PPVT (3)	Age 8 PPVT (4)	Age 12 PPVT (5)
Panel A: First 1000 days					
Number of shocks during the first 1000 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	0.402	0.367
Panel B: By period and type of shock					
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 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 post birth period	-0.599***	-0.130	-3.576*	0.535	5.561*
	(0.085)	(0.116)	(1.898)	(5.675)	(2.932)
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)
Adjusted R2	0.229	0.275	0.593	0.402	0.367
Number of observations	1709	1712	1523	1662	1688
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: Controls include: district fixed effects, year and month-of-birth fixed effects, sex, mother's native tongue, highest schooling level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Index children and siblings included. Standard errors (reported in parentheses) are clustered at district level. * p<0.1 ** p<0.05 *** p<0.01.

7.2. Effects on households' food security

In this sub-section, we explore if the rainfall shocks had an impact on households' food security. More specifically, we measure the effect of shocks on the self-reported Household Food Insecurity Access Scale (HFIAS), included in the YLS data. The HFIAS was constructed as the mean value of a series of dichotomous variables, multiplied by ten (following Vargas and Penny, 2010), forming a continuous scale from 0 to 10. Each dichotomous variable represented the answer to a question related to food insecurity, such as "In the past 12 months, did you ever worry that your household would run out of food?", "Did you or any household member have to reduce the number of meals eaten a day?", etc. The complete list of questions in the questionnaire can be found in Scott (2022). As the HFIAS is a food insecurity scale, the larger the value, the more insecure the household.[26]

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

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

[26] As defined by Vargas and Penny (2010), values between 0 and 2.32 represent a food-secure household. Values between 2.33 and 4.56 represent a household that is food insecure without hunger, between 4.57 and 6.53, a household that is food insecure with moderate hunger, and between 6.54 and 10, a household that is food insecure with severe hunger.

Table 6
Results on Household-level food insecurity.

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 low shocks (in year prior to interview)	0.045***
	(0.014)
Number of abnormally high shocks (in year prior to interview)	0.429***
	(0.119)
Adjusted R2	0.249
Number of observations	2656

Note: Controls include household fixed effects. Analysis performed at a household level. Standard errors (reported in parentheses) are clustered at district level. * p<0.1 ** p<0.05 *** p<0.01.

same community experience the same number of shocks. Due to this limitation, we introduce variation between rounds, within the same household. As the HFIAS questions were included in Rounds 2 and 3, we combine both rounds of answers, and control for household fixed effects. Since our estimations are at the household level (the level at which these 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 6. Panel A reports estimates for the effects of the number of shocks a year prior to the interview, and Panel B divides abnormally low shocks from abnormally high 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. Since the average HFIAS in Round 2 is 2.09, the reported effect of the shock would be enough to shift the HFIAS above the threshold of food security considered by the scale (2.33), driving the average household to a state of food insecurity.

We find results similar in sign both for abnormally low and abnormally high shocks, though the estimated coefficient for the number of abnormally high shocks is almost ten times larger than that for the 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.

One of the main drivers through which rainfall shocks could have affected the available income and the development of cognitive skills is through the impact of shocks on agriculture. The effects of weather on agriculture can reduce the food availability and increase prices, affecting all households in the community. Therefore, agricultural households might be the most vulnerable to these unexpected weather events, as they affect their production directly. We test for differences in the effects between agricultural and non-agricultural households, based on the household main economic activity. More specifically, we estimate fully interactive 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 coefficient of the interaction term between the shock variable and the agricultural household indicator. The results for both the non-interacted shock variables and the interacted variables are reported in Table A6, in the Appendix. The results show no statistically significant differences when comparing the impact on agricultural and non-agricultural households. These results suggest that the weather shocks affect all households in the communities and are not only affecting the incomes of the agricultural producers.

7.3. The role of a major conditional-cash-transfer social program

In this subsection we test if a major public policy could have a role in lessening or remediating the negative effects of early rainfall shocks on FCSs. Particularly, we will focus on the case of Peru's JUNTOS cash conditional transfer (CCT) program. Indeed, Scott et al., (2022) find that receipt of Peru's JUNTOS cash conditional transfer (CCT) program at a relatively younger age is associated with improvements in IC.

There is a growing literature particularly concerned with the role of Conditional Cash Transfers (CCT) as mitigating devices for early life rainfall shocks. Aguilar and Vicarelli (2022) explored the case of the CCT PROGRESA in Mexico, and found that it had no benefits in mitigating the negative effects of rainfall shocks on cognitive development and health. Also studying the case of PROGRESA, Adhvaryu et al. (2024) found that the CCT served to mitigate effects on grade attainment. League and Fitz (2023) use data from Brazil's CCT Bolsa Familia and found that it helps mitigate rainfall shocks during the in-utero period effects on the probability of stunting. Freund et al. (2024) used YLS data and found that Ethiopian recipients of the CCT PSNP manage to offset potential negative effects of rainfall shocks on FCS.

We re-estimate the impact of the shocks during the first 1000 days in the context of the JUNTOS CCT. Taken into account the sample characteristics (some YLS children were benefited by JUNTOS before the age of 5 years, whereas others were benefited when older), we compare 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 dichotompus variable taking the value of one when the child was part of JUNTOS before turning 5 years old, and the other being a dichotomous variable taking the value of one when the child was part of JUNTOS after the age of 5. In the first case, the estimated parameter for the interaction term informs us if being enrolled in the JUNTOS program at an early stage of life helped to reduce the effect of the shock. In the second case, the estimated parameter gives information on the role of the CCT program to remediate shock effects at later stages of life.

We decided to use the age 5 cutoff for reasons related to the program implementation affecting our sample. Since the program started only in 2005, using an early cutoff would have led to the exclusion of all of the index children from the treatment variable, as the youngest index children would have only been 3 years old by 2005. We expected for early interventions to be more relevant than later investments in reducing rainfall shocks, consistent with our conceptual framework. Furthermore, there is evidence of the importance of JUNTOS for positively affecting FCS at younger ages: Scott et al. (2022) shows 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 7 shows the results for heterogeneous effects for children that are part of the JUNTOS CCT programme before and after age 5. We only find significant negative effects of shocks on IC and a remediation effect of JUNTOS for children being part of JUNTOS before age 5. The remediation effect completely offsetting the negative effects of the shock, possibly through an income mechanism. If rainfall has affected FCSs through household income, the cash transfers might help the affected households increase their investments in their children and reduce the effects of the shock.

These results suggest that the programme is more helpful when received at a younger age, which is consistent with our conceptual model predicting early investments being more effective than those at later stages in life, due to accumulative effects through the human-capital accumulation production function. We must be careful interpreting these results, as our results do not remain significant when testing for multiple hypothesis testing and looking at the sharpened q-values. At the same time, our results show no evidence on the potential remediation effect of JUNTOS for those receiving the program later in life.

Overall, our results provide some suggestive evidence of the potential for public policies to remediate the negative impact of rainfall shocks and are consistent with literature suggesting that FCSs might still be malleable at early stages of life (Scott et al., 2022). As the JUNTOS

Table 7
The role of JUNTOS during first 1000 days.

Dependent variable:	Inhibitory Control	Working Memory	Long-Term Memory	Implicit Learning
	(1)	(2)	(3)	(4)
Number of shocks during the first 1000 days	-0.073**	-0.046	-0.041	-0.015
	(0.035)	(0.042)	(0.035)	(0.022)
Number of shocks during the first 1000 days * JUNTOS before age 5	0.098*	-0.016	-0.001	0.117
	(0.058)	(0.069)	(0.053)	(0.089)
Number of shocks during the first 1000 days * JUNTOS after age 5	0.089	-0.062	0.018	0.032
	(0.056)	(0.111)	(0.046)	(0.069)
Adjusted R2	1714	1708	1705	1711
Number of observations	0.376	0.074	0.519	0.325
F-tests (p-values)				
JUNTOS during first 1000 days = after first 1000 days	0.869	0.630	0.718	0.344

Note: Controls include: district fixed effects, year and month-of-birth fixed effects, sex, mother's native tongue, highest schooling level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Index children and siblings included. Standard errors (reported in parentheses) are clustered at district level. * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

program was not randomly allocated, but instead targeted to the "poorest among the poor", we could expect our results to be smaller than those of a causal impact. That is, we could expect higher effects if the results were generalized to the full population, and not only focused on the poorest households in the sample.

8. Discussion and concluding remarks

This paper analyses the longer-term impacts of experiencing rainfall shocks during early childhood on a set of foundational cognitive skills (FCSs) including inhibitory control (IC), working memory (WM), long-term memory (LTM), and implicit learning (IL). We hypothesize 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, and therefore food prices and economic activity in general, 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 FCSs.

By matching novel data on four FCSs from the Young Lives Study with gridded rainfall data at the 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 1000 days of life have long-lasting negative effects on EFs, particularly on WM. When disaggregating the effects by type of shock and periods of the shock, we find that the in-utero effects matter for both WM and IC. While point estimates are larger (in absolute values) for abnormally low compared to abnormally high rainfall shocks, the effects of both types of shocks during this period are undistinguishable statistically. We find no consistent evidence of negative effects of early exposure to rainfall shocks on LTM and IL. We cannot rule out that these effects might have faded away as children aged. The lack of results in this case might also be a consequence of low statistical power as our sample is relatively small.

In terms of the mechanisms of the impact of rainfall shocks on EFs, we observe that shocks increase self-reported food insecurity and reduce childhood nutritional status, which could indicate that rainfall shocks affect FCSs through reductions in investment in human capital when the children are younger and, more specifically, investment in nutrition. We also observe the impact of rainfall shocks was already visible on vocabulary development by 5 years of age, which suggests that early investments in cognitive skills were compromised by these shocks.

Furthermore, our results suggest that there may be space for public policies to remediate the negative effects of rainfall shocks on FCSs. We found that the JUNTOS cash-transfer program might partially compensate for the negative effect of rainfall shocks particularly when treated at early ages. These results strengthen the hypothesis that the rainfall shocks affect the FCSs through decreasing households' incomes and contribute to a growing literature on the potential role of CCTs in alleviate weather shocks.

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. We hypothesize the main mechanism driving our results is related to the rainfall shocks decreasing households' abilities to invest in children's human capital. This study provides some evidence suggesting that this is the case. However, there could be other mechanisms that we cannot observe in the YLS dataset. Future studies should focus on understanding better the mechanisms behind the relationship between early exposure to rainfall shocks and FCSs formation, allowing for the development of better prevention policies to mitigate the negative effects of these shocks in the context of climatic change and poverty.

With climatic change well underway, unpredictable rainfall shocks are becoming more common. These changes tend to affect disproportionately the most vulnerable households, especially those from LMICs. In contexts where 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.

CRediT authorship contribution statement

Alan Sanchez: Writing – review & editing, Validation, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Nicolás Pazos:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Marta Favara:** Writing – review & editing, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Douglas Scott:** Writing – review & editing, Methodology, Conceptualization. **Jere Behrman:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Data availability

The Young Lives data is publicly available through the UK Data Archive. The data and code to replicate our analysis are available upon request

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Appendix

Table A1
Main Results

Dependent variable:	**Inhibitory Control**				**Working Memory**				**Long-Term Memory**				**Implicit Learning**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Number of shocks during the first 1000 days	-0.047*	-0.057*	-0.030	-0.041	-0.047*	-0.053*	-0.066***	-0.090	-0.069*	-0.078*	-0.032	-0.031	0.004	-0.009	0.025	-0.009
	(0.017)	(0.018)	(0.024)	(0.039)	(0.026)	(0.028)	(0.022)	(0.065)	(0.022)	(0.023)	(0.025)	(0.051)	(0.024)	(0.024)	(0.023)	(0.056)
Number of observations	1716	1714	1714	1033	1710	1708	1708	1030	1707	1705	1705	1026	1713	1711	1711	1031
Adjusted R2	0.323	0.346	0.371	0.466	0.029	0.061	0.068	0.118	0.466	0.474	0.482	0.575	0.256	0.306	0.321	0.437
Control variables																
RACER controls**	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RACER Baseline task	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard controls*	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Community level fixed effects	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Household level fixed effects	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

Note: Columns 1–4 correspond to results on Inhibitory Control, columns 5–8 correspond to Working Memory, columns 9–12 correspond to Long-Term Memory, and columns 13–16 correspond to Implicit Learning. Controls include: community fixed effects, year and month-of-birth fixed effects, child's sex, mother's native tongue, highest schooling level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Index children and siblings included. Standard errors (reported in parentheses) are clustered at district level. * p<0.1 ** p<0.05 *** p<0.01.

Table A2
Results under different definitions of shocks

Dependent variable:	**Inhibitory Control**	**Working Memory**	**Long-Term Memory**	**Implicit Learning**
	(1)	**(2)**	**(3)**	**(4)**
Panel A: Results using 6-months rainy season				
Number of shocks during the first 1000 days	-0.024	-0.061***	-0.027	0.021
	(0.023)	(0.018)	(0.021)	(0.023)
Adjusted R2	0.371	0.068	0.482	0.321
Panel B: Results using 1.5 SD shocks				
Number of shocks during the first 1000 days	-0.020	-0.062***	-0.005	0.035*
	(0.017)	(0.013)	(0.023)	(0.021)
Adjusted R2	0.371	0.068	0.482	0.321
Number of observations	1714	1708	1705	1711
Control variables:				
RACER controls**	Yes	Yes	Yes	Yes
RACER Baseline task	Yes	Yes	Yes	Yes
Standard controls*	Yes	Yes	Yes	Yes
Community level fixed effects	Yes	Yes	Yes	Yes
Household level fixed effects	No	No	No	No

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

Table A3
Results on climatic shock perceptions

Dependent variable:	**Reports a drought (R2 and R3)**	**Reports a flood (R2 and R3)**
	(1)	**(2)**
Number of abnormally low shocks (in year prior to interview)	0.129***	0.000
	(0.000)	(0.000)
Number of abnormally high shocks (in year prior to interview)	-0.090	-0.021
	(0.075)	(0.062)
Number of observations	2653	2653
Adjusted R2	0.074	0.012

Note: Standard errors (reported in parentheses) are clustered at district level. * p<0.1 ** p<0.05 *** p<0.01.

Table A4
Results excluding households located in the Jungle

Dependent variable:	Inhibitory Control	Working Memory	Long-Term Memory	Implicit Learning
	(1)	(2)	(3)	(4)
Number of shocks during the first 1000 days	-0.023	-0.079**	-0.051	0.040
	(0.035)	(0.026)	(0.036)	(0.028)
Number of observations	1334	1331	1329	1332
Adjusted R2	0.387	0.066	0.466	0.329
Number of observations	380	377	376	379
Adjusted R2	0.309	0.085	0.553	0.271
Control variables				
RACER controls**	Yes	Yes	Yes	Yes
RACER Baseline task	Yes	Yes	Yes	Yes
Standard controls*	Yes	Yes	Yes	Yes
District level fixed effects	Yes	Yes	Yes	Yes

Note: Controls include: district fixed effects, year and month-of-birth fixed effects, child's sex, mother's native tongue, highest schooling level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Index children and siblings included. Standard errors (reported in parentheses) are clustered at district level. * p<0.1 ** p<0.05 *** p<0.01.

Table A5
Main Results including migrant sample

Dependent variable:	Inhibitory Control	Working Memory	Long-Term Memory	Implicit Learning
	(1)	(2)	(3)	(4)
Number of shocks during the first 1000 days	-0.027	-0.057**	-0.033	0.035
	(0.018)	(0.024)	(0.022)	(0.025)
Number of observations	1828	1822	1818	1825
Adjusted R2	0.377	0.070	0.489	0.322

Controls include: district fixed effects, year and month-of-birth fixed effects, child's sex, mother's native tongue, highest schooling level acquired by parents, whether the child was born prematurely, performance in the baseline tasks, whether the task was administered during the weekend, and the time of the day when the tasks were administered. Index children and siblings included. Standard errors (reported in parentheses) are clustered at district level. * p<0.1 ** p<0.05 *** p<0.01.

Table A6
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 1000 days	-0.042	-0.105**	-0.069**	0.015
	(0.035)	(0.046)	(0.034)	(0.032)
Number of shocks during the first 1000 days * Agricultural household	0.005	0.040	0.028	0.002
	(0.040)	(0.050)	(0.028)	(0.054)
Number of observations	1714	1708	1705	1711
Adjusted R2	0.377	0.063	0.495	0.325

Note: All coefficients are standardized. Controls included: district fixed effects, year and month-of-birth fixed effects, sex, mother's native tongue, 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 district level. * p<0.1 ** p<0.05 *** p<0.01.

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