# El Niño and children: medium-term effects of early-life weather shocks on cognitive and health outcomes

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**Abstract**

Evidence showing that shocks in early life have long-term consequences is well established in the literature. This paper contributes to our understanding of how this develops and what policies could help counteract the shock's impacts. In a development context, we show that four years after being exposed to exogenous precipitation anomalies during early stages of life, children exhibit lower cognitive development (measured through language, working and long-term memory and visual-spatial thinking) in the magnitude of 0.15 to 0.19 SDs. Lower height and weight impacts are also identified. Food consumption and diet composition appear to be key drivers behind these impacts. Partial evidence of mitigation from the delivery of conditional cash transfers is found.

JEL codes: H51, I15, O13, O15, Q54.

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The idea that stimuli or stressful conditions during critical periods in early life can have lifetime consequences is well established in developmental biology (Barker (1998a,b); Bateson (2004)). Known as the *fetal origins hypothesis*, this postulate has been the object of a growing number of studies (Gluckman et al. (2008)). Existing economics literature has been focusing on long-term effects, by examining how pervasive conditions in-utero and during the first years of life have considerable long-term consequences in adulthood (Aizer et al. (2015); Alderman et al. (2006); Almond (2006); Almond and Mazumder (2011); Maccini and Yang (2009); Buser et al. (2014); Scholte et al. (2015); Shah and Steinberg (2017)).

We contribute to the literature by explaining the mechanisms that lead to such long-term consequences. To do this, we show how negative conditions experienced during the early stages of life may affect children's physical, cognitive and behavioral development measured between 2 and 6 years of age. We adopt a quasi-experimental design: our identification strategy relies on exogenous extreme rainfall variations caused by "El Niño Southern Oscillation (ENSO)" during the early stages of an individual's life. To add to the robustness of our estimation, we couple the previous strategy with a difference-in-difference approach employing cohorts of children born after the extreme rainfall events and, thus, not directly exposed to the shock as potential controls.

We spatially combine weather data with a rich longitudinal household survey data collected for the medium-term evaluation of the conditional cash transfer program PROGRESA.[1] PROGRESA's battery of cognitive tests, which include language development, long-term memory, working memory and visual-spatial thinking provides us with high-quality indicators about different areas of early child development. Added to objective anthropometric measures (i.e. height and weight), a test of gross motor skills, and a behavioral assessment, this bundle of indicators greatly advance our knowledge of areas of child development that are both of primary importance and most sensitive to negative early life experiences (Fernald et al. (2008); Macours et al. (2012)). Building upon previous work that has shown that several of these indicators are strong predictors of academic and professional achievements (Case and Paxson (2008); Grantham-McGregor et al. (2007); Currie and Vogl (2013)), we argue that the evidence provided in this paper is a key piece to understand how the early shocks

[1] PROGRESA changed its name to OPORTUNIDADES in 2007, and again to PROSPERA in 2014.

translate to results into adulthood.[2] In addition, the longitudinal component of the dataset allows us to identify possible drivers, through which weather shocks may have affected children's health, development and behavior: namely household income, consumption, and diet composition.

Few studies have attempted to shed light on medium term effects of early life conditions. Leigh et al. (2015) investigate the effect of rainfall shocks in-utero and measure its effects on Chinese and mathematics achievement tests, as well as on measures of self-esteem. They find negative effects in the order of 0.1 to 0.2 SDs that fade out through time. Using Indian data, Shah and Steinberg (2017) find negative effects of weather shocks happening at early stages of development on reading and math test scores as well. Ecuadorian data allows Rosales-Rueda (2016) to assess the possible impact of rainfall shocks on children's height and vocabulary development. She finds that affected children score 0.05 SDs lower in vocabulary and develop 0.03 SDs lower height.

Our paper contributes to this literature in four main aspects: (i) to our knowledge, we provide the most comprehensive list of indicators, covering several topics, (ii) we provide information about potential drivers, such as nutrition, which could be used in the future in the design of mitigation strategies, (iii) we examine the feasibility of conditional cash transfer programs in reducing the vulnerability created by these shocks, and (iv) we base our analysis on a climatic event (ENSO) which climatologists suggest that will become more frequent and intense (Vecchi and Wittemberg (2010); Cai et al. (2014, 2015)).[3]

To identify negative early-life conditions, we employ extreme precipitation shocks[4] that occurred during the 1998-1999 maize harvest seasons, which were impacted by the ENSO

[2]Recent literature has also provided substantial evidence from RCTs about the impacts of child health and nutritional programs on child development (Birch (2000); Hoddinott et al. (2008); Walker et al. (2006, 2007, 2011); Attanasio et al. (2014); Gertler et al. (2014))

[3]ENSO is a recurrent climatic event with a 5 to 7 year cycle. It develops in the Pacific Ocean and affects hydro-meteorological patterns, causing extreme weather events (e.g. droughts, floods, heat waves) with negative impacts on weather-sensitive industries, such as fishing and agriculture Adams (1999). ENSO-related studies are therefore of increasing relevance and urgency from an economic and public policy perspective. Further details about ENSO can be found in *Section 1*.

[4]The terms "extreme precipitation shocks" and "floods" are used interchangeably throughout the paper. Further details about the weather shocks identification are provided in *Section 2*.

climatic event. In rural, rain-fed agricultural settings, rainfall shocks are often cited as the most important risk factor faced by households (PROGRESA-Mexico 1998-99; Fafchamps et al. (1998); Gine et al. (2008)).[5] Using geographical variation in precipitation,[6] we compare children exposed at early stages of life to the shock versus same-aged children not exposed. Rainfall deviations from a location's historical monthly average level is used to identify extreme precipitation events.[7] The population of children under analysis spans different stages of early child development: from *in-utero* conditions up to their second year of life. Our main identification assumption is that the occurrence of these weather shocks is exogenous and creates negative conditions that may potentially affect children at early stages of life. To further improve the robustness of our identification, we employ information from children not born yet at the time of the shock, to build a difference-in-difference estimator.

The main findings in this paper indicate medium-term negative effects of rainfall shocks on cognitive, anthropometric and (possibly) behavioral indicators. On average, children affected between their in-utero development and two years of age exhibit 0.06 standard deviations (SDs) lower weight, 0.05 SDs lower height and higher likelihood of stunting (8.3 percentage points). Language development, working memory, and visual-spatial thinking test scores of these children are 0.19, 0.17, and 0.15 SDs lower than same-aged children not exposed, respectively. These effects are particularly pronounced for children one to two years of life when the shock occurred. No strong evidence of negative effects is found for gross motor skills. As for behavioral indicators, depression and aggression indexes are constructed using mother's self-reported information about children's attitudes. Some estimations suggest impacts on these areas, but less robustly to additional tests.

When investigating the possible drivers of these results, we find that the extreme rainfall events at the end of the harvest season represented an important negative income shock.[8]

[5] Weather events have been widely used in the economics literature as instruments (Hoddinott and Kinsey (2001); Alderman et al. (2006); Baez and Santos (2007); Currie and Rossyn-Slater (2013); Pereda et al. (2014)).

[6] The climatic data used is publicly available from the University of East Anglia Climate Research Unit, (UEA CRU-TS2p1) and includes interpolated monthly time-series from 1961 to 1999, with a spatial resolution of 0.5 x 0.5 degrees (Mitchell (2005)).

[7] This approach is the standard practice in climate science (Heim (2002); Keyantash and Dracup (2004)).

[8] In a technical report, it is also mentioned that the occurrence of these shocks severely compromised crop

Total household income, reported two months after the weather extreme event occurred, was 32 percent lower for households living in regions exposed. This negative income effect persisted at least one year after the event. The reductions in income are confirmed to be mainly driven by lower revenues from agricultural sources. The year after the event, the monetary value of food consumption (per adult equivalents) was 14 percent lower for households in exposed regions compared to households in non-exposed regions. Diet composition presented significant changes too: the year after the extreme event, households in affected regions reported a contraction in their consumption of animal proteins (28 percent), as well as in their consumption of fruits and vegetables (10 percent). Interestingly, food intake measured through total kilograms and calories was not affected, which suggests that households substituted their food intake.

The final part of this paper tests whether PROGRESA's conditional cash transfers helped mitigate the negative effects of the weather shocks. PROGRESA's randomized evaluation coincides in timing with the weather extremes studied in our paper. This regional and temporal coincidence provides a great opportunity to assess PROGRESA's ability to reduce household's and children's vulnerability to shocks. As a second possible identification approach we exploit a discontinuity in the rules employed to select eligible households. This second estimation gives us a longer time of exposure to the program with the limitation of only being able to locally identify the program's effect. With these alternatives, we build DDD and RD-DD estimators. Our analyses find significant evidence of mitigating effects of PROGRESA when the experiment is employed. Nonetheless, the RD-DD estimates do not confirm these findings. This suggests that delivering the program at the time of the shock might have been enough, but that the households marginally eligible for the program display lower impacts of the program.[9]

outputs in Mexico (SAGARPA (2007)).

[9]Paxson and Schady (2008); Fernald and Gertler (2004); Fernald et al. (2008) find slightly positive to no direct effects on anthropometric and cognitive development indicators from randomized poverty alleviation programs in Ecuador (*Bono de Desarrollo Humano*) and Mexico (PROGRESA), respectively. Contrastingly, Macours et al. (2012) investigated the impacts of *Atencion A Crisis*, a randomized cash transfer program in Nicaragua, and found positive effects in development of treated children nine months after the program began.

Our latter result contributes to other strand of literature. Adhvaryu et al. (2015) find that extreme rainfall events in the year of birth have negative impacts on children's educational and later employment outcomes.[10] They also find that children whose families were randomized to receive PROGRESA experienced a much smaller decline in those educational outcomes. Similarly, Duque et al. (2016) use Colombian data and find negative effects of shocks on schooling. They suggest that the Colombian CCT program (*Familias en Acción*) could have helped alleviate the negative effect. Finally, in terms of the drivers we analyze, Vicarelli (2011) findings' confirm that PROGRESA could have insured households against the extreme weather events. We contribute to this literature by showing that the shock's impacts and PROGRESA's potential mitigation covers a wide sphere in terms of human capital development and health, that the timing of delivery of resources matters and that there is heterogeneity in the mitigation impacts.

The remainder of the paper is organized as follows. Section 1 provides some background on ENSO. Section 2 describes the datasets used giving particular emphasis to the child development measures. Section 3 explains the identification strategy. Section 4 details the results of the child development indicators outcomes. Section 5 analyzes the possible mechanisms. Section 6 analyzes and discusses the possible mitigating role of PROGRESA. Finally, section 7 concludes.

# 1 El Niño Southern Oscillation (ENSO)

El Niño Southern Oscillation (ENSO) is a recurrent quasi-periodic climatic event with a 5 to 7 year cycle and global meteorological impacts. It develops across the Pacific Ocean and combines two phenomena: (i) a positive sea-surface temperature anomaly in the eastern tropical Pacific called *El Niño*[11] (or *La Niña* in case of a negative temperature anomaly); and (ii) an atmospheric pressure anomaly in the western tropical Pacific Ocean (i.e the *Southern Oscillation*). ENSO oscillates between its two extremes: *El Niño* (warm event) and *La*

[10] Adhvaryu et al. (2015) focus on individuals in poor households aged 12 to 18 in 2003.

[11] The term *El Niño* is the Spanish expression for *The Child*. It is a religious allegory that refers to the arrival of Child Jesus (or the *Nativity*) because the periodic warming of eastern Pacific, along the coasts of Peru and Ecuador was originally noticed after mid-December, around Christmas.

*Niña* (cold event). *El Niño* and *La Niña* events tend to differ for onset, magnitude, spatial coverage, duration and cessation (Ropelewski and Halpert (1987); Philander (1990); Allan (2000)). Each phase typically lasts one year, with a peak in December, and then tapers down towards a neutral state (Rasmusson and Carpenter (1982)).

ENSO affects hydro-meteorological patterns. This influences the frequency and intensity of tropical storms, including a decrease (increase) in Atlantic hurricane activity (Gray (1984)) and an eastward (westward) shift of western Pacific cyclone activity during *El Niño* (*La Niña*) (Revell and Goulter (1986); Chan (2000)). Thus, ENSO typically results in extreme weather events such as droughts, floods, and heat-waves (Ropelewski and Halpert (1987); Philander (1990); Neelin et al. (1998); Larkin and Harrison (2001, 2005)). There is evidence suggesting that ENSO cycles have occurred for more than 6,000 years (Markgraf and Diaz (2000)), and will continue to occur and influence global climate in the future. Moreover, ENSO events might become more frequent and more intense during the 21st century in response to climate change (Allan and Soden (2008); Vecchi and Wittemberg (2010); Cai et al. (2014); Wu et al. (2013)). Therefore, it is of great interest to understand the nature and magnitude of ENSO-related weather extremes' impacts on society.

ENSO periodically causes severe socioeconomic consequences in both developed and developing countries: the estimated costs of the two largest *El Niño* events of the twentieth century were: 8 to 18 billion U.S. dollars (USD) for the 1982-83 event (UCAR (1994); Sponberg (1999)), and 35 to 45 billion USD for the 1997-98 event (Sponberg (1999)). Its strongest impacts are experienced in countries bordering the Pacific Ocean, from Latin America to Southeast-Asia (Cane et al. (1994)). In developing countries, weak or absent insurance and credit markets make households employed in weather-sensitive industries (e.g. agriculture and fishing) particularly vulnerable.

For this paper, data was collected from Mexican poor rural areas where most of the households depend directly or indirectly on agriculture. Most of the farmers surveyed report growing maize –the most important crop in Mexico– under a rain-fed system (close to 90% of the households).[12] Maize has two main agricultural seasons: Spring-Summer (78.5% of total

[12] Between 1996-2006, maize production amounted for 51% of the surface planted, generated 7.4% of the total agricultural volume produced, and represented 30% of the value of total production.

production) and Autumn-Winter (21.5%) (SAGARPA (2007)). In this paper we focus on the Spring-Summer season, which develops in three main stages: (i) planting (April-June), (ii) growing (July-August), and (iii) maturation and harvesting (September-November). Conde et al. (2004) indicate that April's rain is fundamental for a successful maize crop. If rain doesn't arrive by May, farmers usually switch their crop to other varieties that develop faster and have shorter cycles (mainly oat, which can be planted up to June).[13] Later, the growing season is vulnerable to lack of rain (Smith et al. (1991), Amendola et al. (2005)). Finally, the harvest season, which is the one we focus on in this study, is sensitive to hurricanes and flooding events (SAGARPA (2007); Vicarelli (2011)).

# 2 Data

Two main data sources were used in this paper. The main dataset corresponds to the PROGRESA's randomized evaluation longitudinal database. It was collected biannually between 1997 and 2000 at 506 marginalized communities of rural Mexico. In 2003, a follow-up survey gathered specific information about children between 2 and 6 years old from 259 villages, 5,000 households, and 6,264 children. The 2003 data included anthropometric, health, cognitive, and gross motor development indicators.[14] Information about precipitation was added to this dataset using geographical identifiers. *Table 1* shows descriptive statistics about the main outcomes, the weather data and some controls that will be used in the analysis. In this section, we discuss in detail the indicators used from each data source.

[13] A popular Mexican farmer's rhyme describes this behavior: "What Saint John doesn't see born (June 24th), Saint Peter considers lost (June 29th)" (authors' translation to the original: "Lo que San Juan no ve nacido, San Pedro lo da por perdido").

[14] Data is publicly available at `https://prospera.gob.mx/EVALUACION/es/eval_cuant/p_bases_cuanti.php`

Table 1: Descriptive statistics

| Variable | Num. obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Anthropometrics and health** | | | | | |
| weight (lb) | 4111 | 34.1628 | 6.5819 | 16.3142 | 122.1359 |
| height (in) | 4111 | 38.4246 | 3.4115 | 16.8110 | 56.4567 |
| stunting (binary) | 2912 | 0.3448 | 0.4754 | 0 | 1 |
| anemia (binary) | 4111 | 0.7497 | 0.4332 | 0 | 1 |
| sick days | 4111 | 1.3262 | 2.6411 | 0 | 30 |
| **Cognitive tests** | | | | | |
| language (std) | 3339 | 0.0138 | 0.9855 | -1.1708 | 5.4739 |
| LT memory (std) | 4111 | 0.0495 | 1.0123 | -1.1284 | 4.5431 |
| ST memory (std) | 4111 | 0.1387 | 0.9337 | -1.9120 | 3.0769 |
| visual-spatial (std) | 4111 | 0.0688 | 0.9717 | -1.4832 | 4.8456 |
| **Motor skills and behavioral** | | | | | |
| McCarthy score (std) | 4111 | 0.0757 | 0.9199 | -2.779 | 0.991 |
| balance (seconds) | 4111 | 6.8285 | 3.5829 | 0 | 10 |
| walk back (binary) | 4111 | 0.9115 | 0.2841 | 0 | 1 |
| walk str (binary) | 4111 | 0.8613 | 0.3456 | 0 | 1 |
| depression (std) | 4111 | -0.0149 | 0.9942 | -1.4753 | 2.7044 |
| aggression (std) | 4111 | 0.0376 | 0.9923 | -2.3023 | 1.7594 |
| **Controls** | | | | | |
| age (months) | 4111 | 49.9606 | 13.0276 | 22 | 74 |
| male (binary) | 4111 | 0.49 | 0.50 | 0 | 1 |
| HH head language | | | | | |
| * spanish & indigenous | 4111 | 0.3490 | 0.4767 | 0 | 1 |
| * only indigenous | 4111 | 0.0248 | 0.1555 | 0 | 1 |
| **Rainfall Measures** | | | | | |
| Precip. Oct 1998 (SPI) | 4111 | 0.6191 | 0.5182 | -0.4676 | 1.7105 |
| Precip. Oct 1999 (SPI) | 4111 | 0.8656 | 0.8649 | -1.1043 | 2.7824 |
| Rain Shock 1998 | 4111 | 0.6699 | 0.4703 | 0 | 1 |
| Rain Shock 1999 | 4111 | 0.5999 | 0.4900 | 0 | 1 |

Units are indicated in parenthesis. “Std” indicates if the variable has been standardized with respect to the sample. “Binary” indicates if the variable is a dummy. “SPI” corresponds to rainfall differences in standard deviations with respect to each grid-month long-term mean (calculated over 1961-1999).

## 2.1 Progresa Data

During the 2003 PROGRESA data collection, internationally recognized tests were gathered on a group of children aged 2 to 6.[15] The complete set of variables constitutes a rich array of child development indicators with information on both child physical and cognitive development. Analyzing the effect of early life shocks on these indicators may provide valuable insights on factors driving the long-term impacts identified in the existing literature (e.g. Almond (2006); Maccini and Yang (2009)). Also, these type of measurements are rare in a developing context, but even more unique is the fact that we can connect it to the shock occurrence under analysis and to a longitudinal dataset that will allow us to complement our study by looking at potential channels.

The main outcomes under analysis and some background about factors impacting development areas measured by those outcomes are described next:

### 2.1.1 Cognitive Development Indicators

**Receptive vocabulary.** Measured with the *Peabody Picture Vocabulary Test* (PPVT), receptive vocabulary refers to words a child understands. Receptive vocabulary and grammar development are usually environmentally driven; and for preschool children they are mostly determined by the family environment. Empirical evidence suggests that vocabulary tests are strong predictors of school success, and that receptive vocabulary contributes in a large extent to general intelligence assessment scores (Stevenson and Newman (1986)). The PPVT test is used in preschool aged children by asking them to indicate which of four pictures best represents a stimulus word (Dunn and Dunn (1981)).

**Long-term and working memory.** Long-term memory storage and retrieval abilities are measured with a section of the *Batería III Woodcock-Muñoz Test*[16] (WMT), which requires children to remember associations between an increasing number of unfamiliar auditory and

[15]The tests used stand out for their *internal reliability* and *validity*. In educational testing, *internal reliability* indicates the degree to which test scores for a group of test takers are consistent over repeated applications of the measurement procedure (AERA (1999), pp. 180). *Validity* refers to the degree to which accumulated evidence and theory support specific interpretations of the test scores (AERA (1999), pp. 184.).

[16]The Spanish version of the Woodcock-Johnson Test.

visual stimuli (i.e. memory for names of novel cartoon characters) and be able to later retrieve them (Schrank (2010)). The measured indicator is associated with both long-term and working memory. *Long-term memory* is the ability to store information and fluently retrieve it later. *Working memory*, also called phonological loop, plays an important role in long-term phonological learning[17] and short-term storage (Baddeley (2000)). These dimensions are associated with the development of vocabulary in children, and with the speed of acquisition of foreign language vocabulary in adults (Baddeley (2000); Baddeley et al. (2003)). Deficits in working memory have been associated to low birth weight (Isaacs et al. (2000)), pre-term birth (Woodward et al. (2005)), as well as poor nutrition in-utero and in early life (Georgieff (2007)).

**Short-term memory.** This concept refers to the ability to temporarily store and reproduce verbal and/or visuo-spatial information that has just been presented (also generally referred to as memory span). It is measured in a section of the WMT test by requiring children to remember and repeat lists of unrelated words in the correct sequence. Children with short-term memory impairments will typically also have difficulties in learning new verbal information such as a new vocabulary, new definitions, and in learning associations between abstract concepts (Baddeley et al. (2003); Majerus and Van der Linden (2013)). Short-term memory impairments are usually associated to cerebral damages or genetic syndromes. Nutrition has not been evidenced to present long-term effects on short-term memory (Baddeley et al. (2003); Majerus and Van der Linden (2013)).[18] Therefore, this indicators could serve

[17]Phonological learning involves becoming aware of sounds of spoken language (phonological awareness), holding that information in working memory (phonological memory), accessing phonological information, retrieving that information (retrieval of phonological codes), and making associations between sounds and printed symbols (e.g., alphabetic letters) (Joseph (2011)).

[18]According to Majerus and Van der Linden (2013), the observation of a selective short-term memory impairment, in the absence of any other cognitive deficit due to cerebral damage (most often as a result of a cerebro-vascular accident, which is rare in children) or genetic syndromes, is extremely rare. A number of genetic syndromes are characterized by poor short-term memory spans, either for verbal short-term memory, such as in Down syndrome (trisomy 21) or for visual short-term memory, such as in Williams syndrome (7q11.23) and X-related syndromes (Fragile X, Turner syndrome, Klinefelter syndrome and Rett syndrome) (Majerus and Van der Linden (2013)). Lastly, short-term memory disorders are most often observed in

in our study as a control, unless severe effects are observed.

**Visual-spatial thinking.** This concept is also measured as part of the WMT by asking children to identify spatial relations by selecting an object's picture from a partial drawing or representation. This concept measures the ability to perceive, analyze, synthesize, and think with visual patterns, including the ability to store and retrieve visual associations. This ability is related to working memory; hence like working memory it may be affected by poor nutrition in early life. Visual spatial thinking abilities may contribute to later success in: mathematical abilities (Geary (1993, 2004)), integrating ideas, problem solving skills, abstract thinking and learning of conceptual subjects (Hegarty and Kozhevnikov (1999); Van Garderen (2006)).

### 2.1.2 Anthropometric indicators.

Objective measures of child physical development, such as *height* and *weight* are useful indicators of balanced nutrition and overall child health. As part of the 2003 data collection, certified nurses measured this information from children. *Stunting*, or low weight for age, is constructed based on the WHO definition.[19] Stunting usually reflects insufficient nutrient intake during early stages of development. It generally occurs before age two and once established, it is usually permanent (most children never gain the height lost nor achieve a normal body weight). Consequences may be extremely severe: a stunted growth may lead to premature death later in life due to incomplete development of vital organs during childhood. Less extreme effects also include delayed development, impaired cognitive function, and poor school performance (UNICEF (2007)).

### 2.1.3 Health indicators.

Blood samples were gathered for all children. By using hemoglobin levels, adjusted for village altitude, an indicator for *anemia* is generated based on the WHO standards (Ruiz-Argüelles

association with broader cognitive impairment: children with specific language impairment and children with dyslexia typically show poor verbal short-term memory and working memory spans.

[19]Equal to *one* if the child's height is two or more standard deviations below the age-sex standardized height of a healthy reference population (WHO (1996)).

and Llorente-Peters (1981)). *Anemia* is usually an indicator of poor nutrition (mainly iron deficiency) and poor health. Its negative consequences range from lower cognitive and physical development to increased risk of mortality (WHO (2008)). An additional measure of child's health is the number of *sick days*. Mothers were asked to self-report the number of days that their children were sick during the previous month and unable to perform their regular activities.

### 2.1.4 Gross motor skills indicators

Gross motor skills were evaluated using a section of the *McCarthy Scale of Children's Abilities* (MSCA) (McCarthy (1972)). The MSCA focuses on leg coordination for children between 2 and 6. Children are required to complete multiple exercises, such as (i) standing on one foot, (ii) walking forward in a straight line, (iii) walking backward, (iv) tip-toeing, and (v) jumping rythmically. The outcomes of the activities are combined into a single *McCarthy indicator* using principal component analysis. Difficulty or inability to perform the actions assessed can be debilitating for young adults in rural areas and could have broad long-term socioeconomic consequences. Deficiencies in gross motor coordination (e.g. poor balance, poor timing and coordination, difficulty combining movements into controlled sequences) may also reflect neuromotor and executive-function deficits (Wilson and McKenzie (1998); Polatajko and Cantin (2005)).

### 2.1.5 Behavioral indicators: Anxiety/Depression and Aggressive Behavior

An assessment based on the *Achembach Child Behavioral Checklist* (CBCL) (Achenbach and Rescorla (2001)) provides a measure of *internalization behavioral problems* (i.e. anxiety and depression) and one of *externalization problems* (i.e. aggressive behavior). Internalization and externalization behavioral problems can be detected since infancy (Barham (2012)). The CBCL is a caregiver-rating checklist where a range of behaviors are classified by its frequency of occurrence.[20] Answers are combined to build behavioral indicators. Child psychology literature suggests that early identification of behavioral and emotional problems

[20] Behaviors are assessed through statements, such as "The child cries a lot", "The child is talkative", "The child is anxious", etc.

is important. Behavioral and emotional problems in early childhood have been shown to be stable over time, but early detection has been shown to lead to successful early intervention efforts (Bagner et al. (2012)).

Empirical evidence suggests that stressful environmental conditions and poor nutrition in early childhood may be related to behavioral and emotional problems in childhood, youth, and adulthood (Galler et al. (2010); Liu et al. (2004)). In particular, severe protein deficiency in childrens' diets between 9 and 24 months of age seem to have a strong association with both growth stunting and increased symptoms of depression and low self-esteem in adolescents (Galler et al. (2010); Walker et al. (2006, 2007)).[21] Other studies in this literature have also found that malnutrition predisposes to neurocognitive deficits, which in turn leads to persistent externalizing behavior problems throughout childhood and adolescence (Liu et al. (2004)). To our knowledge, little research in the economics literature has used behavioral assessments, even though recent literature suggests that psychosocial and biological risk factors may contribute to child development and long-term adult productivity (Fernald and Gertler (2009); Grantham-McGregor et al. (2007); Walker et al. (2007)).

#### 2.1.6 Income and nutrition

Finally, the panel component of the PROGRESA dataset includes information about household's income level as well as its diet composition. Income can be distinguished by revenue source, which we employ to revise the effects on agriculturally-originated income. Diet composition originates from questions asked to the households about their specific consumption during the week before the survey. Food consumption is split by vegetables, fruits, meat, mains staples (such as tortilla, eggs, milk). All these variables are reported at the households level, which does not allow us to distinguish who in the household is consuming such items. These information was gathered roughly every six months between 1997 and 2000.

[21] For example, Galler et al. (2010) focuses on the effects of an episode of *marasmus*, that is, moderate-severe malnutrition arising from the lack of protein, energy, and other nutrients, as well as the effects of an episode of *kwashiorkor*, a lack of protein only, which was limited to the first year of life. Their findings are in line with reports from Jamaica confirming an association between growth stunting (linear growth retardation) that occurred between 9 and 24 months of age and increased symptoms of depression (Walker et al. (2006, 2007)).

## 2.2 Weather and Climate Data

To measure the presence of rainfall shocks in the regions under analysis, we use monthly precipitation data available from the University of East Anglia Climate Research Unit (UEA CRU -TS2p1). The monthly series are available as interpolated gridded data with pixels of size 0.5 x 0.5 degrees (Mitchell (2005)). This dataset is spatially merged with the PROGRESA dataset using the geographical location of the village where each child was born. The 259 PROGRESA villages are distributed over 55 grid-cells. The number of villages per grid-cell varies, from a minimum of 1 to a maximum of 20. By spatially joining climate and village data we are able to assign to each village the climate time series of the underlying pixel.

Our main variable of interest is the *standardized precipitation anomaly.* It is calculated for each grid-month pair as the difference in the rainfall level with respect to the grid-month long-term mean (calculated over the period 1961-1999) and expressed in standard deviations. The use of this measure is widely accepted in the climatology literature, referred to as the Standardized Precipitation Index (SPI), for the quantification of droughts or excessive precipitation (Heim (2002); Keyantash and Dracup (2004))[22].

The SPI presents a major strength compared to absolute measures of precipitation. Interpreting the magnitude of the precipitation deficit/excess can be challenging because precipitation climatology (i.e. long-term mean) varies widely over geographical regions as well as temporal scales. Standardizing precipitation anomalies with respect to the long-term mean is therefore an important step to make sure that the level of the precipitation deficit or excess is judged relative to some climatological norm for the location.[23] Thus, the measure should be understood as deviations with respect to the normal precipitation conditions. This measure has also been widely adopted in the economics literature to identify weather shocks (Adhvaryu et al. (2015); Deschenes and Greenstone (2006); Maccini and Yang (2009); Shah

[22]The SPI captures the accumulated deficit (SPI $< 0$) or surplus (SPI $> 0$) of precipitation over a specified period (in our study, one month), and provides a normalized measure of relative precipitation anomalies at multiple time scales. World Meteorological Organization, (2012) Standardized Precipitation Index User Guide (M. Svoboda, M. Hayes and D. Wood). (WMO-No. 1090)

[23]Keyantash, John & National Center for Atmospheric Research Staff (Eds). Last modified 08 Mar 2018. “The Climate Data Guide: Standardized Precipitation Index (SPI)." Retrieved from https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-index-spi

and Steinberg (2017)).

In addition of using the SPI itself, we also employ a binary variable to identify ENSO-related rainfall shocks ($rain\_shock$) to analyze the impact of negative conditions during early stages of life. A rainfall shock is identified whenever the *standardized precipitation anomaly* is above 0.7 standard deviations during the 1999 harvest months (September or October).[24] The decision to use a binary variable for the rain shocks was motivated by two main reasons: (i) the use of the binary variable aids the ease of interpretation of the results; and (ii) qualitative evidence suggests that crop loss can result from one flood event rather than as a result of precipitation accumulation throughout the month, making the relation between crop output and rainfall not easily fitted with a parametric functional form.

*Figure 1* maps the SPI for October 1999 in the region of interest and displays the classification for the rainfall shock dummy for localities in our sample.[25] We chose to focus in the extreme rainfall events at the end of the 1999 agricultural season because of the high degree of spatial rainfall variability observed at the harvest season, which was preceded by normal rainfall levels during the planting period.[26] We argue that extreme rainfall shocks at the end of the agricultural season are analogous to negative income shocks for the household given that all the investment of labor and resources had already been spent on the crop. Evidence collected from the households in the database suggests that these shocks were unexpected: households do not report significant changes of land use or total hectares planted at the beginning of the season when comparing households in regions affected versus not affected by the weather shocks. Thus, households in our dataset do not seem to be able to forecast, adapt or quickly react to ENSO events. Moreover, the use of the SPI measure ensures that this is not a recurrent situation for the localities that experienced larger levels of rainfall during our period of analysis.[27]

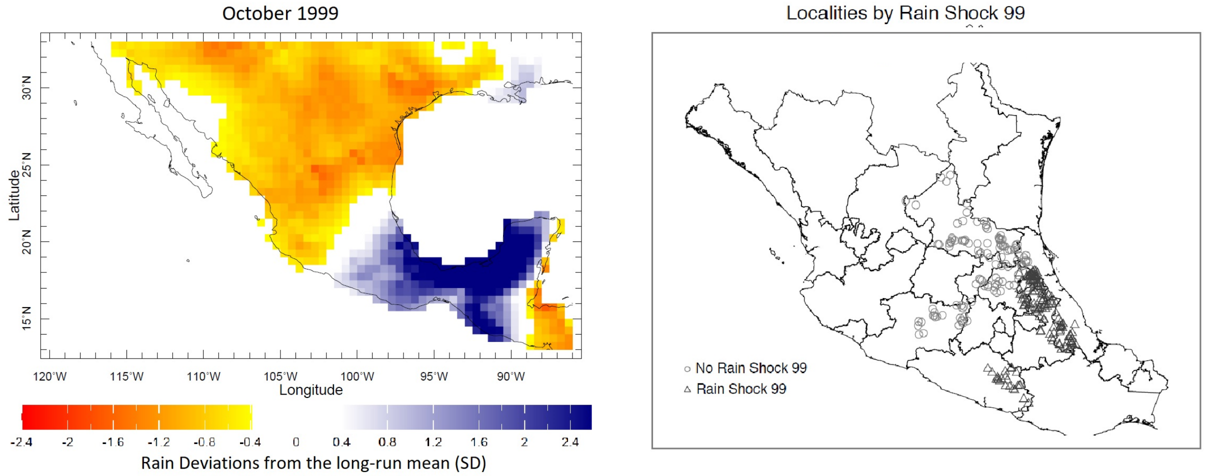
[24] A *standardized precipitation anomaly* above 0.5 and below 0.84 represents moderately wet conditions and may be associated with localized intense precipitations within a gridcell. We therefore pick 0.7 as cutoff point to identify *rainfall shocks*.

[25] The graph illustrates the distribution of the *standardized precipitation anomalies* with respect to the 1961-1999 historic averages for the different grids.

[26] *Figure A.1* in the appendix shows the SPI distribution for the 1998 and 1999 agricultural season months. Only data for the gridcells of interest was employed to create this graph.

[27] Precipitation patterns during *El Niño* and *La Niña* events do not repeat themselves in a consistent way

Figure 1: Distribution of the standardized precipitation anomalies and rain shocks




The left-hand map shows the spatial distribution of rain anomalies (standard deviations with respect to their long-term mean) in the region of interest in October 1999. Each pixel is 0.5 x 0.5 degrees. The right-hand map displays the localities in our sample and shows the rain shock classification that we use in our main analysis. Each locality marked with a △ (○) corresponds to a locality with rain levels above (below) 0.7 SDs and is thus classified as a locality where a rain shock did (not) occur in 1999. *Figure A.3* shows the geographical distribution that would result of using 1998 for our analysis.

# 3 Empirical Specification

The main identification assumption is that the occurrence of the shocks is exogenous and generated negative conditions that affected children at early stages of life. The key variables are location and timing. Timing is established through the difference between date of birth and the date of the shock. In our main specification, the date of the shock is September-October 1999, which corresponds to the harvest season. Location is determined by the geographical areas where the rain shocks created weather anomalies. We begin our analysis by estimating a parametric relation between standardized precipitation anomalies and the outcomes of interest as follows:[28]

$$Y_{ijt} = \eta_t + \alpha_1\ rain\_SD_j + \alpha_2\ rain\_SD_j^2 + \beta\ X_{ijt} + \epsilon_{ijt} \tag{1}$$

at the local level. On the contrary, as shown in *Figure A.2*, the spatial distribution of extreme precipitation changes from one event to the next in a rather unpredictable way.

[28]Different functional forms were explored and the results are consistent with those presented here. We decided to keep a quadratic form for illustration purposes and because we were interested to explore if the concavity and maximum/minimum values made intuitive sense with respect to the rain anomalies. Nonetheless, in the graphs used to report these results, conditional means were also added for transparency.

where $Y_{ijt}$ is the outcome for individual $i$ in pixel $j$ born in year $t$; $rain\_SD_j$ is the rain precipitation anomaly in pixel $j$ during September-October 1999; $\eta_t$ accounts for cohort fixed effects; and $X_{ijt}$ are controls for individual $i$ in pixel $j$.

To strengthen our analysis we employed a cohort of children not directly exposed to the shock as a control group and a dummy variable to identify the shock occurrence (as detailed in section 2.2) to build a difference-in-difference estimation:

$$Y_{ijt} = \gamma_1 \text{ coh97-00}_t + \gamma_2 \; rain\_shock_j + \gamma_3 \text{ coh97-00}_t \cdot rain\_shock_j + \beta \; X_{ijt} + \epsilon_{ijt} \tag{2}$$

where $\text{coh97-00}_t$ indicates if the individual was born in years 1997 to 2000 (the reference group being born in 2001); $rain\_shock_j$ is a dummy indicating if a weather shock occurred in 1999 at pixel $j$.[29] All estimations include Conley spatially-correlated standard errors with 1 decimal degree cutoff (Conley (1999)).[30] In this specification, $\gamma_3$ is our main parameter of interest and measures the impact of the rain shock.

We further explore in detail the effects by birth cohort by employing the following specification:

$$Y_{ijt} = \eta_t + \gamma_2 \; rain\_shock_j + \left( \sum_{k=1997}^{2000} \theta_k \; coh\_k_{it} \cdot rain\_shock_j \right) + \beta \; X_{ijt} + \epsilon_{ijt} \tag{3}$$

where $coh\_k_{it}$ is a dummy variable indicating if the individual $i$ was born in year $k$. In this specification, $\theta_k$ represents the difference-in-difference estimator of the impact of the shock by cohort of birth.

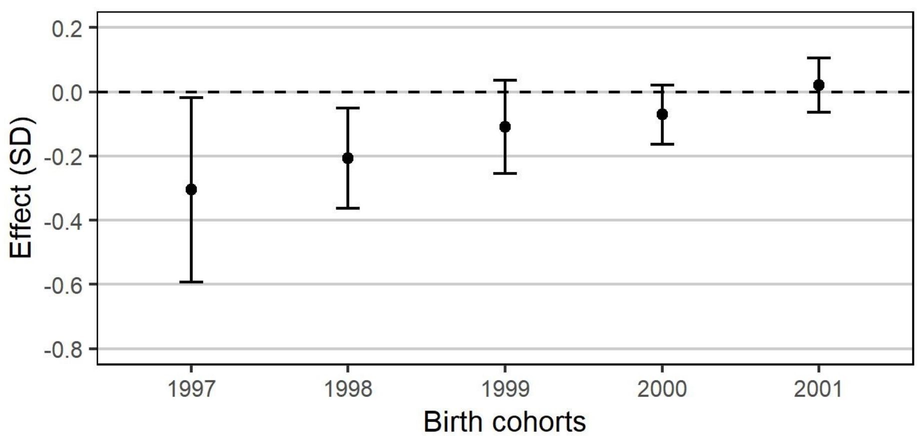
These specifications seek to identify the medium-term effect of excessive rainfall shocks occurring at early stages of children's development on anthropometric, health, behavioral and cognitive outcomes. The main parameters of interest ($\gamma_3$ and $\theta_k$) estimate the effect of the shock for children in a given development stage with respect to same-aged children that were not affected by the shock. For instance, $\gamma_3$ in equation (2) captures the impact of the shock on individuals exposed during their in-utero development or first years of life. Equation (3) breaks this effect by birth cohort. For example, $\theta_{1997}$ will give the effect of the shock on

[29] In the appendix we show an additional exercise where we employ the rain shock (under the same definition) that occurred in 1998.

[30] Sensitivity analyses using clustered standard errors at the pixel level or Conley standard errors with a threshold of 2 decimal degrees are shown as part of our robustness tests.

children that were one to two years old at the time of the shock. All our previous estimates are constructed using children born one to two years after the occurrence of the shock (cohort 2001) as a control group. These children are closer to not being affected by the shock unless the effects were more persistent, in which case our estimations should be interpreted as giving differential estimates of the shock with respect to the 2001 cohort which was the least exposed. Figure 2 illustrates how the estimates from equation 3 should be understood. In this graph we use the long-term memory test as an outcome. The graph displays the effects of the shock by birth cohort. Here, $\theta_{1997}$ would correspond to the difference in the effect of cohort 1997 with respect to 2001.

Figure 2: Effects of the rain shock on long-term memory by birth cohort.




This figure exemplifies the construction of the difference-in-difference estimates. The dot for cohort 2001 corresponds to the estimated value of $\gamma_2$ from equation 3. The dots for cohorts 1997-2000 correspond to the estimated values of $\gamma_2 + \theta_k$ for $k = \{1997, \ldots, 2000\}$. Confidence intervals are constructed using Conley standard errors with a cutoff values of one degree. The example displayed corresponds to using the Woodcock-Muñoz test for working and long-term memory (WM1). Thus, each dot is measured in standard deviations of the test results. The results in panel A in Table 3 correspond to the average between the weighted averages for cohorts 1997-2000 with respect to the effect of cohort 2001. The results in panel B correspond to the differences between each cohort with respect to cohort 2001.

**Exogeneity Test** To test the assumption of exogeneity of the shocks we exploit the longitudinal nature of the dataset. The PROGRESA pilot survey baseline data collected household information in 1997, before the 1999 rainfall shock took place.[31] *Table 2* shows the difference of means for villages exposed to the rainfall shock and villages not exposed to the rainfall shock for a group of indicators. The statistics show that, at baseline, for most observable

[31] The survey's original purpose was to collect baseline information before the PROGRESA program pilot implementation started in 1998.

characteristics there is no significant difference between villages affected and not affected by the rainfall shocks. However, households where the head belongs to an indigenous group[32] seem to be more likely to be affected by the weather shock. Our empirical model takes this into account by controlling for the indigenous identity of the head of the household. We also performed robustness checks using as control variables, those whose differences in Table 2 are statistically significant at the usual levels. Results of the robustness checks are discussed in Section 4.5.

# 4 Main Results

## 4.1 Effects on cognitive development

As mentioned in *section 2*, the pediatric neurology literature suggests that poor nutrition in-utero and early life, may cause significant deficits on working memory and other cognitive abilities (Georgieff (2007)). Short-term memory, on the other hand, represents a useful control for our analyses since negative impacts would occur only in more extreme situations involving cerebral damages or genetic syndromes (Majerus and Van der Linden (2013); Baddeley et al. (2003)).[33]

We begin our analysis by broadly exploring the relation between the standardized precipitation anomaly and the cognitive outcomes. *Figure 3* plots the estimates from equation 1.

[32]Head of household speaks only and indigenous language or speaks both Spanish and an indigenous language

[33]According to Majerus and Van der Linden (2013) , the observation of a selective short-term memory impairment, in the absence of any other cognitive deficit due to cerebral damage or genetic syndromes, is extremely rare. Short-term memory disorders are most often observed in association with broader cognitive impairment: children with specific language impairment and children with dyslexia, for example. A number of genetic syndromes are also characterized by poor short-term memory spans. In summary, the literature seems to indicate that in-utero and early-life nutrition does not have an important role in the development of short-term memory. In relation with nutrition, one research question that has drawn much attention is the effect of intake/omission of breakfast on cognition in children. The literature seems to suggest that breakfast omission deteriorates the short-term mental performance, but does not seem to have long-term impacts (Bellisle (2004)).

Table 2: Exogeneity tests for excessive rainfall shocks. Columns (1) and (2) present the mean values of each variable for villages not-exposed to rainfall shocks ($rain\_shock_j = 0$) and exposed to rainfall shocks ($rain\_shock_j = 1$), respectively. Column (3) and (4) report the difference of the two means and the corresponding t-statistics.

| | Mean $rain = 0^{\mathrm{a}}$ (1) | Mean $rain = 1$ (2) | Difference (3) | p-value (4) |
|---|---|---|---|---|
| **Village characteristics** | | | | |
| male avg. wages | 315.33 | 301.00 | -14.33 | 0.519 |
| female avg. wages | 42.09 | 43.73 | 1.64 | 0.779 |
| **Household characteristics and assets** | | | | |
| size | 5.54 | 5.76 | 0.22 | 0.134 |
| Poverty index | 720.33 | 721.57 | 1.24 | 0.949 |
| owns land (ha) | 1.51 | 1.52 | 0.01 | 0.975 |
| own house (binary) | 0.92 | 0.90 | -0.02 | 0.353 |
| electricity (binary) | 0.75 | 0.76 | 0.01 | 0.865 |
| running water (binary) | 0.05 | 0.04 | -0.01 | 0.647 |
| tv (binary) | 0.58 | 0.46 | -0.12* | 0.059 |
| vehicle (binary) | 0.12 | 0.07 | -0.05* | 0.054 |
| monthly income (pesos) | 4841.83 | 4006.75 | -835.08 | 0.352 |
| donkeys | 0.39 | 0.37 | -0.03 | 0.800 |
| sheep | 1.43 | 1.21 | -0.22 | 0.738 |
| chickens | 6.45 | 7.17 | 0.72 | 0.447 |
| **Household migratory characteristics** | | | | |
| temporary migrants | 0.23 | 0.15 | -0.07* | 0.057 |
| permanent migrants | 0.02 | 0.02 | 0.00 | 0.905 |
| remittances (monthly pesos) | 20.07 | 23.45 | 3.38 | 0.838 |
| **Head of household characteristics** | | | | |
| male (binary) | 0.88 | 0.86 | -0.02 | 0.278 |
| age (years) | 38.01 | 37.57 | -0.44 | 0.735 |
| education (years) | 3.80 | 3.41 | -0.39* | 0.084 |
| agric worker (binary) | 0.67 | 0.71 | 0.04 | 0.520 |
| Indigenous language spoken | 0.27 | 0.58 | 0.31** | 0.017 |

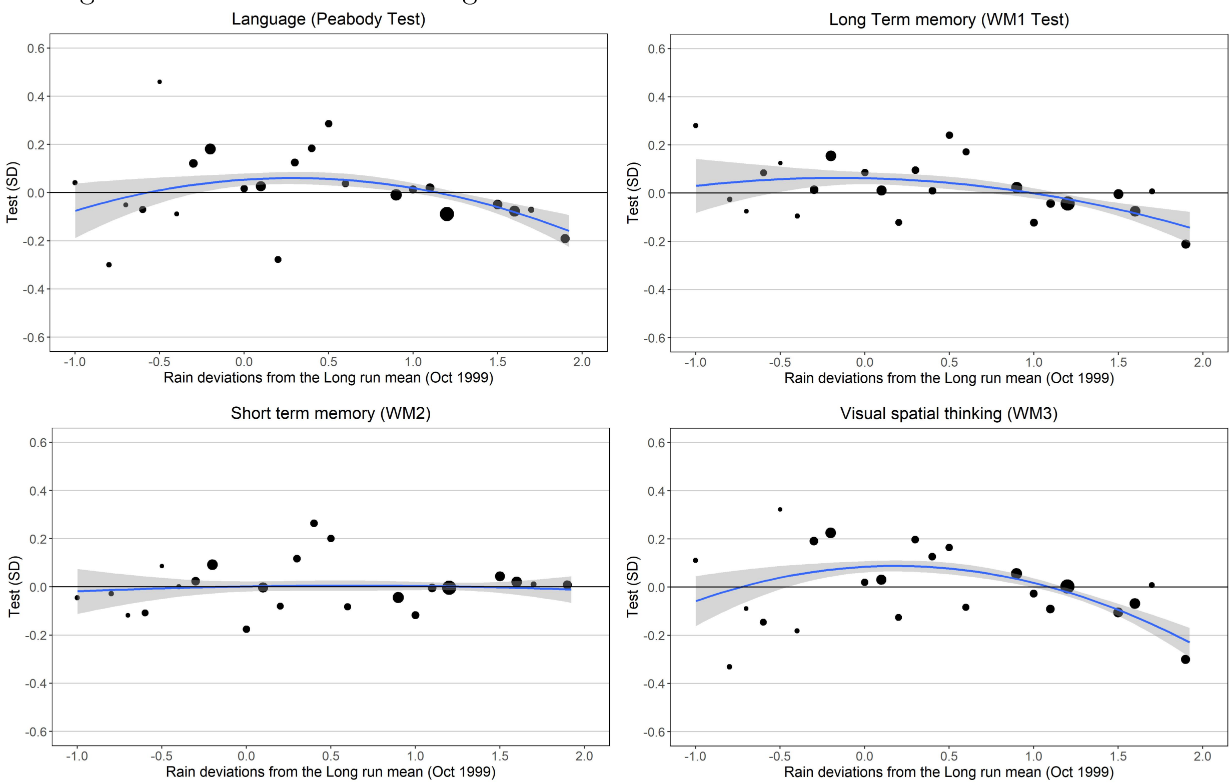
Conley standard errors in parentheses (cutoff= 1 degree). Significant at the * 10%, ** 5%, *** 1% level.
[a] The rainfall shock is defined as the rainfall in a given grid in September or October 1999 being 0.7 standard deviations above its long-term (1961-1999) average

The figure restricts observations to the cohorts of children affected by the shock.[34] Interestingly, by using a quadratic parametric estimation, we find a clear relation between abnormal levels of precipitation and the cognitive outcomes for all our metrics, except the short-term

[34] In contrast, the relations are not evident for the 2001 cohort. Graphs available upon request.

memory test. In particular, positive levels of precipitation anomalies (that could potentially have led to floods), display the lowest levels in the cognitive test scores. Also, the graphs show how normal conditions match with the maximum in all the parametric estimates.

Figure 3: Relation between cognitive outcomes and rain anomalies in October 1999.




These figures show the relation between rain anomalies (SD with respect to the long-term mean) in October 1999 and the cognitive outcomes. *Peabody Test* measures language development. *Woodcock-Muñoz Test* is used to assess a set of cognitive abilities: working and long-term memory (WM1), short-term memory (WM2) and visual-spatial thinking (WM3). Each dot in the graph represents a conditional mean using a bin size of 0.1 SDs. The size of each dot is proportional to the number of observations in the bin. Each outcome was previously partialled-out using an OLS estimation of each corresponding outcome versus our main set of controls (*age* (months), $age^2$, *gender*, *father's language*, and *cohort fixed effects*). The line is the result of a quadratic OLS estimation as detailed by equation 1. The gray region around the line represents a 95% confidence interval.

*Table 3* reports the estimated effects of excessive rainfall shocks during the 1999 harvest season on cognitive outcomes using the difference-in-difference specifications. The estimates suggest negative and significant effects of the rainfall shocks on language development (equal to 0.19 SDs on average), long-term and working memory (0.17 SDs), and marginally non-significant effects on visual-spatial thinking abilities (0.15 SDs, p-value = 0.105). The larger negative effects are mostly found on children affected by the shock during their first or second year of life (i.e. children born in 1997 and 1998). Children born in 1997 exhibit lower test scores on the language, long-term and working memory, and visual-spatial thinking tests, by respectively 0.61, 0.33, and 0.28 SDs, with respect to same aged-children not affected by the shock. The effects on children born in 1998 are lower in absolute value - compared to 1997 - but still of considerable magnitude; test scores on the language, long-term and working memory, and visual-spatial thinking tests are respectively 0.21, 0.23, and 0.19 SDs lower than scores for same aged-children not affected by the shock. Children who were exposed to the shock close to their birth or during their in-utero development (i.e. born in 1999 and 2000) exhibit smaller, and mostly non-significant effects. All this effects are estimated using the difference-in-difference estimator (equation 3) with respect to children born two years after the shock. The 2001 cohort does not display any significant differences between children affected and not-affected by the shock in any of these dimensions.

Consistently with the results from *Figure 3*, the only cognitive outcome that does not display statistically significant differences in children between the affected and non-affected is the short-term memory test. As detailed above, this indicator is expected to be negatively affected from a developmental perspective only in more extreme situations. The results show a negative non-significant effect of the shock, which suggest that it might be affecting only a few extreme cases.

## 4.2 Effects on anthropometric and health indicators

*Table 4* presents the estimated effects of rainfall shocks using the difference-in-difference estimation on children's anthropometric indicators (*height*, *weight*, and a binary indicator for *stunting*), and health outcomes (a binary indicator for *anemia*, and self-reported *number of sick days* during the previous month).

Results show significant lower weight and height for children that were exposed during the first two years of life to the shock. On average, they exhibit 0.096 to 0.196 standard deviations (SDs) lower weight and 0.094 to 0.108 SDs lower height with respect to same-aged children not exposed. The negative impacts on height are substantive enough to significantly increase the probability of stunting. On average, affected children have an 8.3 percentage point higher likelihood to suffer stunting in comparison to same-aged children not affected by the shock. Such effect is slightly more pronounced in children affected during their in-utero

Table 3: Effect of the 1999 September-October rainfall shock on cognitive development indicators measured in 2003 for children born between 1997 and 2000. (Outcomes are standardized test scores).

| | **Peabody Test**[a] | **Woodcock-Muñoz Test**[b] | | |
|---|---|---|---|---|
| | language | working/long term memory | short term memory | visual spatial thinking |
| | (1) | (2) | (3) | (4) |
| **Panel A** | | | | |
| coh97-00 × rain_shock[c] | -0.189** | -0.174*** | 0.013 | -0.150 |
| | (0.0762) | (0.0640) | (0.0635) | (0.0926) |
| **Panel B** | | | | |
| coh97 × rain_shock[d] | -0.613*** | -0.326** | 0.028 | -0.275* |
| | (0.1499) | (0.1316) | (0.0837) | (0.1553) |
| coh98 × rain_shock | -0.208* | -0.228*** | 0.009 | -0.191 |
| | (0.1075) | (0.0853) | (0.0681) | (0.1205) |
| coh99 × rain_shock | -0.020 | -0.129 | -0.010 | -0.096 |
| | (0.0616) | (0.0845) | (0.0637) | (0.0909) |
| coh00 × rain_shock | | -0.092** | 0.039 | -0.099 |
| | | (0.0459) | (0.0810) | (0.0670) |
| Observations | 3339 | 4111 | 4111 | 4111 |
| $R^2$ | 0.3369 | 0.2599 | 0.4985 | 0.4212 |
| Mean | 0.014 | 0.050 | 0.139 | 0.069 |

Controlling for *age* (months), *age*$^2$, *gender*, *father's language*, and *cohort fixed effects*.
Conley standard errors in parentheses (cutoff= 1 degree). Significant at the * 10%, ** 5%, *** 1% level.

[a] *Peabody Test* measures language development. Peabody test scores are a reliable predictor of achievements in primary school.

[b] *Woodcock-Muñoz Test* is used to assess a set of cognitive abilities: working and long-term memory, short-term memory and visual spatial thinking.

[c] *coh97-00 × rain_shock* indicates the DiD estimate of the *rain_shock* impact for birth cohorts 1997-2000 with respect to the 2001 birth cohort (which was less or close to non-exposed to the 1999 rain shock). The only exception is the Peabody result (column 1). Peabody was not implemented to cohort 2001, therefore the variable *coh97-00 × rain_shock* really indicated the comparison between birth cohorts 1997-1999 with respect to 2000. The rainfall shock is defined as the rainfall in a given grid in September or October 1999 being 0.7 standard deviations above its long-term (1961-1999) average.

[d] Panel B disaggregates Panel A by yearly cohorts. Each *cohXX × rain_shock* coefficient shows the DiD estimate of the rain shock for each given cohort with respect to the 2001 cohort (the least exposed cohort) with the exception of Peabody (column 1) where birth cohort 2001 was not tested and differences are calculated with respect to the 2000 birth cohort. The only exception is the Peabody result, where the DiD estimates correspond to the comparison with respect to cohort 2000.

development.[35] Finally, there is no evidence suggesting that anemia and children's number of sick days (self-reported by their mothers) are significantly affected by the weather shocks.

*Figure A.4* in the appendix shows a similar graphical analysis as the one presented in *Figure 3*. Consistently with the analysis in the previous subsection, it is possible to see

[35] The lower number of observations for the stunting indicator is explained by the fact that WHO tables that standardize children's height with respect to a reference population were used to generate this indicator. Such tables are only available for children up to 5 years of age. The previous height indicator is normalized with reference to the PROGRESA sample to provide observations for all children in our base sample.

Table 4: Effect of the 1999 September-October rainfall shock on anthropometric indicators, measured in 2003, for children born between 1997 and 2000.

| | Weight (Z)[a] (1) | Height (Z)[a] (2) | Stunting[b] (3) | Days_sick[c] (4) | Anemia[d] (5) |
|---|---|---|---|---|---|
| **Panel A** | | | | | |
| coh97-00 ×rain_shock[e] | -0.056 | -0.052 | 0.083* | -0.036 | -0.009 |
| | (0.0383) | (0.0387) | (0.0488) | (0.2584) | (0.0444) |
| **Panel B** | | | | | |
| coh97 ×rain_shock[f] | -0.196* | -0.108 | | 0.306 | -0.019 |
| | (0.1035) | (0.0733) | | (0.3106) | (0.0527) |
| coh98 ×rain_shock | -0.096* | -0.094** | 0.078 | 0.030 | -0.047 |
| | (0.0569) | (0.0413) | (0.0652) | (0.2566) | (0.0489) |
| coh99 ×rain_shock | -0.058 | -0.012 | 0.074 | -0.226 | 0.005 |
| | (0.0467) | (0.0451) | (0.0514) | (0.3114) | (0.0506) |
| coh00 ×rain_shock | 0.054 | -0.020 | 0.094* | -0.058 | 0.017 |
| | (0.0388) | (0.0488) | (0.0556) | (0.3186) | (0.0444) |
| Observations | 4111 | 4111 | 2912 | 4111 | 4111 |
| $R^2$ | 0.4713 | 0.6978 | 0.0555 | 0.0057 | 0.0572 |
| Mean | 0.109 | 0.132 | 0.345 | 1.326 | 0.750 |

Controlling for *age* (months), *age*$^2$, *gender*, *father's language*, and *cohort fixed effects*.
Conley standard errors in parentheses (cutoff= 1 degree). Significant at the * 10%, ** 5%, *** 1% level.
[a] *Weight* and *height* are measured by trained nurses and standardized with respect to the sample used for the estimations.
[b] *Stunting* is a binary variable = 1 if the child is stunted. Stunting is defined as being two or more standard deviations below the age-sex standardized height with respect to a healthy reference population [WHO (1996)].
[c] Number of days in the previous 4 weeks that the child was self-reported sick by the mother.
[d] *Anemia* is a binary variable = 1 if the child is anemic. Anemia is defined as hemoglobin less than 11 g/dL adjusted for altitude [WHO (2008)].
[e] *coh97-00* × *rain_shock* indicates the DiD estimate of the *rain_shock* impact for birth cohorts 1997-2000 with respect to the 2001 birth cohort (which was less or close to non-exposed to the 1999 rain shock). The rainfall shock is defined as the rainfall in a given grid in September or October 1999 being 0.7 standard deviations above its long-term (1961-1999) average).
[f] Panel B disaggregates Panel A by yearly cohorts. Each *cohXX* × *rain_shock* coefficient shows the DiD estimate of the rain shock for each given cohort with respect to the 2001 cohort (the least exposed cohort).

that the lowest levels in weight and height are found for locations with higher standardized precipitation anomalies and that the higher values are found in localities with normal conditions. Anaemia also has a parametric relation that suggest that localities with higher deviations from their long-run averages are most affected, although the variability evident from the graph explains why non-significant differences were found for this outcome. Finally, self-reported sick-days has a flat relation with respect to the precipitation anomalies.

## 4.3 Effects on gross motor skills

Work in the medical literature indicates that severe malnutrition in the early stages of life may be related to gross motor skills delays (Walker et al. (2007)). *Table 5*, shows the results from analyzing the possible relation between weather shocks and motor skills with the difference-in-difference approach. No statistically significant effects are found using the motor skills indicator (the McCarthy index) or the balance indicator. We also analyze the possible effect of weather extremes on each component of the MSCA indicator. Table A.1 disaggregates the McCarthy test results for each exercise that the children are requested to complete. Our analysis shows that there is some heterogeneity in the success rate and variation associated to the exercises. For instance, walking backwards has a high degree of success (91%), while keeping the balance on one foot and jumping rhythmically have the highest degree of variation. However, our results suggest that the weather shocks did not have any significant effects on any of the motor skills tested using the MSCA. *Figure A.5* in the appendix also shows a relatively flat relation between the motor skills outcomes and the standardized precipitation anomaly.

## 4.4 Effects on behavioral indicators

*Table 5* also shows the results of the difference-in-difference estimation when using the two CBCL indicators described in *section 2*. The *anxiety and depression* index does not display statistically significant effects while the *aggressive behavior* index shows negative effects for children one to two years of age at the time of the shock and for the in-utero cohort, both in the order of $0.23 - 0.25$ SDs. This result reflects an increase in aggression for children affected by the shock. In contrast, *Figure A.5* in the appendix suggests that the standardized precipitation anomaly seems to be mostly impacting children in the *anxiety and depression* dimension since the behavior of the index is similar to the cognitive and anthropometric outcomes previously identified as affected by the shock. A closer look to the results using this outcome shows that every cohort seems to be affected by the shock, which leads to a null effect when employing the difference-in-difference estimation. Meanwhile, *Figure A.5* displays a flatter relation when using the *aggressive behavior* index.

Table 5: Effect of the 1999 September-October rainfall shock on gross motor skills and behavioral outcomes, measured in 2003, for children born between 1997 and 2000. (Outcomes for McCarthy test scores, depression and aggression indexes are standardized).

| | **McCarthy**[a] | | **Achenbach CBCL**[b] | |
|---|---|---|---|---|
| | McCarthy Score (1) | Balance (Dummy) (2) | Anxiety & Depression (3) | Aggressive Behaviour (4) |
| **Panel A** | | | | |
| coh97-00 × rain_shock[c] | 0.071 | 0.010 | 0.001 | -0.146 |
| | (0.0894) | (0.0366) | (0.0781) | (0.1015) |
| **Panel B** | | | | |
| coh97 × rain_shock[d] | 0.163 | 0.040 | 0.010 | -0.245* |
| | (0.1004) | (0.0497) | (0.1157) | (0.1415) |
| coh98 × rain_shock | 0.104 | 0.013 | -0.032 | -0.130 |
| | (0.0922) | (0.0382) | (0.1006) | (0.1206) |
| coh99 × rain_shock | 0.052 | 0.012 | -0.028 | -0.072 |
| | (0.0936) | (0.0499) | (0.0708) | (0.1006) |
| coh00 × rain_shock | 0.014 | -0.009 | 0.082 | -0.227* |
| | (0.1064) | (0.0448) | (0.1019) | (0.1168) |
| Observations | 4111 | 4110 | 4111 | 4111 |
| $R^2$ | 0.4241 | 0.2608 | 0.0147 | 0.0066 |
| Mean | 0.076 | 0.503 | -0.015 | 0.038 |

Controlling for *age* (months), *age*$^2$, *gender*, *father's language*, and *cohort fixed effects*.
Conley standard errors in parentheses (cutoff= 1 degree). Significant at the * 10%, ** 5%, *** 1% level.

[a] *The McCarthy Scale of Children's Abilities* Test measures children's motor skills development. The test requires children to complete a set of exercises. The outcome used combines the tests into a single indicator calculated using PCA. Balance is a dummy indicating if the child was able to hold its balance on one foot for more than 10 seconds in each in both, left and right foot.

[b] *The Achenbach Child Behavioral Checklist* is a set of questions related to the child behavior that are answered by the child's main caregiver [Achenbach and Rescorla (2001)]. Answers are combined in two indicators of two possible types of behavioral problems: internalization behavioral problems (*Anxiety and Depression*), and exernalization behavioral problems (*Agressive Behavior*).

[c] *coh97-00* × *rain_shock* indicates the DiD estimate of the *rain_shock* impact for birth cohorts 1997-2000 with respect to the 2001 birth cohort (which was less or close to non-exposed to the 1999 rain shock). The rainfall shock is defined as the rainfall in a given grid in September or October 1999 being 0.7 standard deviations above its long-term (1961-1999) average).

[d] Panel B disaggregates Panel A by yearly cohorts. Each *cohXX* × *rain_shock* coefficient shows the DiD estimate of the rain shock for each given cohort with respect to the 2001 cohort (the least exposed cohort) with the exception of Peabody (column 1) where birth cohort 2001 was not tested and differences are calculated with respect to the 2000 birth cohort.

Tables A.2 and A.3 disaggregate the *anxiety and depression* and *aggressive behavior* indexes by examining separately each of the questions from the *Achenbach Child Behavioral Checklist*. The results from this analysis suggest that the question most influenced by the 1999 shock towards the *anxiety and depression* index results is: "*does your child feel nervous often?*". Only this question displays a significant differences (at the 5% level). As for the *aggressive behavior index*, the questions that seem to be driving the detected effect are: (i) *is your child cruel or mean to others?*, and (ii) *does she/he often disobeys?* In general, the results with questions related to physical aggression seem to drive the effect found with the difference-in-difference estimation.

The results from the behavioral indicators outcomes suggest that weather shocks could have partially affected children's cognitive abilities through the behavioral channel too. Stress in early life was found to be associated with deficits in a range of cognitive (cognitive performance, memory, and executive functioning) and affective functions (reward processing, processing of social and affective stimuli, and emotion regulation) (Pechtel and Pizzagalli (2011); Lupien et al. (2009)). Although our results in this area are less conclusive than those in the cognitive dimension, we believe these results invite for further exploration in future work.

## 4.5 Robustness checks

### 4.5.1 Reduced-form estimates

Given that our main assumption for identification is the exogeneity of the standardized precipitation anomaly, the reduced-form estimates of the *rain shock* indicator should be sufficient to identify the impact of the weather shock. If the shock by itself has a persistent effect, our difference-in-difference estimates should underestimate the true impact of the shock. We employ the difference-in-difference estimates as our main results since we consider them to be the most robust, although potentially the most conservative as well.

Panel B in *Tables A.4, A.6* and *A.8* shows the reduced form estimates by displaying separately the impacts of the rain shock in cohorts 1997-2000 and cohort 2001 ($\gamma_2 + \gamma_3$ and $\gamma_2$ in equation 3, respectively). The results confirm that, if anything, the difference-in-difference estimates might be underestimating the effects on cognitive outcomes (in the order of 0.01 to 0.02 SDs) and anthropometric outcomes (between 0.05 and 0.07 SDs).

### 4.5.2 Adding controls to the main specification

The exogeneity test presented in *Table 2* supports our main identification assumption with 23 variables. Of these 23, 5 variables present statistically significant differences in means between villages exposed to the weather shock and villages not exposed. As a robustness test, we repeated our estimations by adding the 5 variables as additional controls. If our initial estimates presented in tables 3, 4, and 5 are capturing confounding effects, it is likely that these additional control variables will pick up some of that effect, thus altering the main coefficients. Panel C in *Tables A.4, A.6* and *A.8* shows that the main estimates do not change significantly when these additional controls are added and thus provide reassuring evidence for our main claim.

#### 4.5.3 Using the 1998 rain shock

*Figure A.3* shows the comparison between the geographical distribution of the standardized precipitation anomaly and the rain shock definition shock in 1998 versus 1999. As can be seen, an important geographical overlap exists in the distribution of the precipitation anomaly between both years. Panel D in *Tables A.4, A.6* and *A.8* show the results of using either the 1998 rain shock occurrence or both 1998 and 1999 shock. As can be seen from the tables, the effects of both scenarios are very similar to those from 1999 as it would be expected from observing the distribution of the precipitation anomaly in the maps.

#### 4.5.4 Sensitivity to the geographical identification strategy

Our identification using the difference-in-difference specification employs as a *treatment* variable the rain shock event. Since the definition of the rain shock is geographical, such is an important part of the variation being employed. The correlation between close-by locations results on affected and non-affected localities being clustered. This is made evident in *Figure A.3*, which shows the geographical distribution of the shocks. A concern of this clustering is that, despite the affected and not affected regions do not appear to be very different ex-ante in terms of observables as shown in *Table 2*, they could be in unobservables. Employing the difference-in-difference specification makes our specification more robust to this concern (with respect to the reduced-form estimation) since such unobservables should differentially affect cohorts exposed and not-exposed to the shock to impact the parallel trend assumption.

Still, employing the geographical distribution of the shock, we add a robustness test by redoing the main specifications while removing two regions: (i) in the first case we remove all the localities in the State of San Luis Potosi, which is the state most to the north, (ii) in the second case we remove all the localities in the States of Guerrero and Michoacan, which are the states in the Pacific coast and tend to be poorer. Figure A.6 shows the regions being removed for these tests and the remaining localities being used in the specifications.

Panel E in *Tables A.5, A.7* and *A.9* summarize the results from this test. The results are slightly sensitive to the removal of these states, although the main effects remain. For instance, the cognitive effects are most sensitive to the removal of the poor states, although the effect on working/long term memory remains identified at the 10% level, while the visual-spatial thinking is marginally not-significant. The removal of these poor states in turn does not affect the anthropometric outcomes, if anything, the effects are stronger. The removal of the northern State does not affect any of the results. Finally, Figure A.2 in the appendix confirms that the standardized precipitation anomaly measure tends to be clustered geographically, but does not always impact the same regions in different ENSO events. This supports our geographical exogenous variation assumption.

#### 4.5.5 Conley versus clustered standard errors

A final robustness test we considered was using a larger radius for the Conley standard errors and clustered standard errors at the pixel level for comparison. Panel F in *Tables A.5, A.7* and *A.9* displays the comparison of using either of these errors. As can be seen, the different errors are very similar and the significance is not greatly affected. If anything, the errors selected for our main scenarios tend to be larger, thus being the most conservative choice.

## 5 Mechanisms Driving the Results

This section explores some of the mechanisms that might be driving the medium-term effects of the rain shock on children's development. We exploit the longitudinal design of the database, spanning three years from 1998 to 2000, to analyze immediate and persistent effects of the weather shock on household dimensions that may affect the child's growing environment. The following specification is used to estimate the effect of the rainfall shock on possible mechanisms. The underlying assumption for the identification is the exogeneity of the shock.

$$Y_{hjt} = \gamma_0 + \gamma_1 \; rain\_shock_j + \beta X_{hjt} + \epsilon_{hjt} \tag{4}$$

where $Y_{hjt}$ represents the level in household $h$ in pixel $j$ at year $t$ for the indicator of the potential mechanisms under analysis; $rain\_shock_j$ is the dummy indicating if the shock occurred in pixel $j$ in 1999 and $X_{hjt}$ are a set of controls. Here, it is not possible to use a difference-in-difference specification as in equation (2). There is no reference cohort because our analysis is done at the household level and every household in regions affected by the shock could have been impacted. Thus, we show the result from the reduced-form estimation. The main parameter of interest is $\gamma_1$.

*Tables 6* and *7* show the main results of the mechanisms analysis. The main dimensions of the mechanisms explored are the following.

**Income** In response to shocks, households experienced considerable income reductions. We estimate the effect of rainfall shocks on total household income and income from agricultural activities measured in the year of the shock and one year after the shock. The estimates indicate that households exposed to the shock have lower total income than those not affected, being the effect persistent until the next period (up to two periods in our estimates with the 1998 shock). The results shown in *Table 6* indicate a lower income ranging between 27% and 32%. This reduction is primarily driven by lower agricultural income, a reduction that ranges between 25% and 33% for households in affected regions with respect to those in non-affected regions. Estimates not shown (available upon request) give evidence that previously to the shock, individuals in both regions planted their crops in the same intensity. This supports the idea that the shock was unexpected.

**Government aid** Post-shock governmental food and non-food aid might help smooth consumption, particularly food consumption. The PROGRESA dataset allows us to assess if villages exposed to shocks are more likely to have benefited from government transfers. We find that the probability of receiving government food aid increases by 7% immediately after the shock for households living in affected villages. Other government programs also had a

10 percentage point higher likelihood or benefiting households in affected regions the year of the shock. This shows that the government acted upon the shock to try to ameliorate the effects of the event. Nevertheless, this effort does not seem to have neutralized the negative effect of the shocks on medium-term children's outcomes.

**Informal transfers** In rural villages, informal insurance strategies aimed at smoothing post-shock consumption include food and non-food transfers from relatives or neighbors. The results indicate significant reductions in the probability of receiving informal transfers from family members after the shock in the order of 1.4 percentage points. Neighbor support also seems to decrease, although the 0.9 percentage point contraction found is not significant at the usual levels. Weakening of these transfers may be explained by the fact that family and neighbors were also exposed to the rain shock.

**Consumption and diet composition** Rainfall shocks may affect child physical and cognitive development through malnutrition. Income constraints, paired with absence of formal insurance and credit markets, and the weakening of informal safety nets (e.g. family and intra-village transfers), led to consumption contractions. Non-food consumption is usually the first portion of household consumption to be reduced. When these reductions are insufficient to protect food consumption and savings are not available, households must inevitably reduce the value of their food consumption, often by adopting changes in their diet composition or even by reducing their food intake.

We estimate the effect of excessive rainfall shocks on food consumption and in diet composition. Results in *Table 7* show contractions in the value of food consumption equal to 6% (non-significant) in the period of the shock and 14% the year after.[36]

Interestingly, the reduction in the monetary value of food consumption was accompanied by non-significant changes in overall food consumption measured by total quantities (kg) or calories. This suggests that important dietary shifts towards a cheaper basket might have happened. Three main changes in diet composition were also found in households exposed

[36] These results are consistent for the 1998 shock. For those estimations, it can be seen that the reduction in value of food consumption lasts up to two years after the shock.

Table 6: Effect of the 1999 rainfall shock on overall income, agricultural income and probability of receiving formal and informal aid. Estimates contemporaneous to the shock ($t$) and one year after the shock ($t+1$) are shown.

| Dependent Variables | Binary Variable (✓)[a] | Coefficient[b] | Std_Dev |
|---|---|---|---|
| **Total household income (log)** | | | |
| $income_t$ | | -0.315*** | (0.0596) |
| $income_{t+1}$ | | -0.273*** | (0.0565) |
| **Household income from agriculture (log)** | | | |
| $agricultural\_income_t$ | | -0.331*** | (0.0630) |
| $agricultural\_income_{t+1}$ | | -0.247*** | (0.0612) |
| **=1 if household received government aid** | | | |
| $food\_aid_t$ | ✓ | 0.073*** | (0.0157) |
| $other\_aid_t$ | ✓ | 0.101** | (0.0437) |
| **=1 if household received informal transfers[c]** | | | |
| $from\_family_t$ | ✓ | -0.014** | (0.0044) |
| $from\_neighbor_t$ | ✓ | -0.009 | (0.0060) |

Conley standard errors in parentheses (cutoff= 1 degree). Significant at the * 10%, ** 5%, *** 1% level.
[a] Indicates if the dependent variable is a dummy.
[b] Each line shows the result of a different regression where equation (4) is estimated and the dependent variable is the one indicated in the first column. Control variables include *household's head age*, *gender*, *education*, *language spoken*, and *number of HH members*.
[c] This corresponds to any kind of cash transfers received by any relative members (from family), friends or neighbors.

to the shock. First, consumption of tortillas[37] increased immediately after the shock by 11%, but later decreased by 14% (these results are non-significant using 1999 shock and significant at usual levels using the 1998 shock). Second, consumption of animal-origin products decreased by 14% (NS) and 28% in these periods. Lastly, consumption of fruit and vegetables decreased by 10% (NS) in period after the shock.

The shift towards cheaper foods and a low-protein diet, by privileging tortillas over the consumption of nutritious foods rich in animal proteins (e.g. meat, fish, eggs, milk), might have had negative consequences on the health conditions, brain development and overall development of young children (Walker et al. (2007, 2011); Morgane et al. (1993)).

[37] Maize tortillas are the main food staple in Mexico

**Health of household members and medicine expenditures** Worse health conditions for children in household exposed to weather shocks immediately after the shock might point to health as a possible channel for the medium-term results. *Table 7* presents estimates of the impact of the rainfall shock on two health-related measures: the proportion of children reported sick by the mother within each household (*children_sick*) and medicine expenditures (*medicine_expenditure*) immediately after the weather shock and up to one year after its occurrence. The results seem to suggest that health conditions reported by the mother were not affected and that medicine expenditures decreased for households exposed to shocks by 13 to 15% in the period of the shock and the following one, respectively. Nonetheless, it is possible that medicine expenditure are driven by liquidity constraints rather than changes in health status.

# 6 Progresa's potential mitigating effects

In 1997, villages in the region under analysis were selected to be included in PROGRESA, a widely known governmental conditional cash transfer (CCT) program. By design, it included a randomized program evaluation that took place between 1997 and 2000 (Skoufias (2001); Behrman et al. (2005)). Eligibility for the program was determined based on this index and a pre-determined threshold.[38] Eligible households in treatment communities were notified of their selection for the program and most of these families started receiving the benefits around May of 1998. Less than two years later, between January and May 2000, eligible households from the control communities were incorporated into the program. (Skoufias et al. (1999); Coady (2000); Fernald and Gertler (2004)) This section investigates the potential mitigating effects against the negative consequences of exposure to the 1999 rainfall shock for households eligible to receive PROGRESA.

[38] The threshold, the variables used for the index and the weights to construct the index were not known by the beneficiaries nor by local authorities. This prevents households to lie and strategically answer the survey to get into the program.

Table 7: Effect of the 1999 rainfall shock on food consumption, diet composition, child health and medicine expenditure. Estimates contemporaneous to the shock ($t$) and one year after the shock ($t+1$) are shown.

| Dependent Variables | Coefficient[a] | Std_Dev |
|---|---|---|
| **Food consumption (log)[b]** | | |
| $food\_consumption_t$ [pesos] | -0.059 | (0.0397) |
| $food\_consumption_{t+1}$ [pesos] | -0.138* | (0.0707) |
| $food\_consumption_t$ [kg] | 0.044 | (0.0477) |
| $food\_consumption_{t+1}$ [kg] | 0.024 | (0.0876) |
| $food\_consumption_t$ [calories] | 0.069 | (0.0430) |
| $food\_consumption_{t+1}$ [calories] | 0.033 | (0.1071) |
| **Diet composition (log)** | | |
| $tortilla\_consumption_t$ [pesos] | 0.111 | (0.0957) |
| $tortilla\_consumption_{t+1}$ [pesos] | -0.140 | (0.1030) |
| $animal\_consumption_t$ [pesos] | -0.142 | (0.1160) |
| $animal\_consumption_{t+1}$ [pesos] | -0.278** | (0.1165) |
| $fruit\_and\_vegetable\_consumption_t$ [pesos] | 0.006 | (0.0706) |
| $fruit\_and\_vegetable\_consumption_{t+1}$ [pesos] | -0.104 | (0.0676) |
| **Children reported sick[c] by the mother** | | |
| $children\_sick_t$ (% in the HH) | 0.032 | (0.0350) |
| $children\_sick_{t+1}$ (% in the HH) | -0.034 | (0.0299) |
| **Medicine Expenditure (log)** | | |
| $medicine\_expenditures_t$ | -0.132 | (0.1319) |
| $medicine\_expenditures_{t+1}$ | -0.151* | (0.0868) |

Conley standard errors in parentheses (cutoff= 1 degree). Significant at the * 10%, ** 5%, *** 1% level.

[a] Each line shows the result of a different regression where equation (4) is estimated and the dependent variable is the one indicated in the first column. Control variables include *household's head age*, *gender*, *education*, *language spoken*, and *number of HH members*.

b Food consumption is self-reported by the household and based on a detailed set of questions about their consumption during the previous week. It includes self-consumption of crops grown by the household. Monetary value for consumption is calculated using median food prices from the village, municipality or state (the least aggregated, conditional on having at least 20 prices observed). Kilograms are self-reported and calories are proxied by the authors based on a FDA guidelines and typical products found on Mexican grocery stores.

[c] Sickness is self-reported based on the question if the child was not able to perform its typical activities some day during the last week.

## 6.1 Using the randomized experiment

Most of the previous work related to PROGRESA has taken advantage of the randomization. Behrman and Todd (2000) shows that households in control and treatment localities are balanced. Our first empirical estimation to assess the potential mitigating effects of PROGRESA follows the line of the randomized control trial. It is important to keep in mind that the control villages were added to the program in 2000. The randomization then potentially protects households at the time of the shock, but permanent effects in the mechanisms would be less effectively identified.

Adding the random distribution of the program to our difference-in-difference estimation from equation (2), we build a triple difference estimation (DDD):

$$\begin{aligned} Y_{ijt} = \gamma_1 \text{ coh97-00}_t + \gamma_2\ rain\_shock_j + \gamma_3\ Progresa_j + \gamma_4 \text{ coh97-00}_t \cdot rain\_shock_j + \dots \\ + \gamma_5\ Progresa_j \cdot \text{coh97-00}_t + \gamma_6\ Progresa_j \cdot rain\_shock_j + \dots \\ + \gamma_7\ Progresa_j \cdot \text{coh97-00}_t \cdot rain\_shock_j + \beta\ X_{ijt} + \epsilon_{ijt} \end{aligned} \tag{5}$$

where with respect to equation (2) we add the variable $Progresa_j$, which indicates if village $j$ was randomly receiving PROGRESA at the time of the shock. Here, $\gamma_7$ is our parameter of interest, which represents the potential mitigation of the program.

*Table 8* presents the DDD mitigation estimates of PROGRESA. The evidence from the table suggests that there is a mitigating effect in the anthropometric outcomes affected by the shock (height and weight). In addition, *anaemia* seems also to be benefited by the delivery of the program. With respect to the cognitive outcomes, there only seems to be a mitigating effect on language development. The rest of the cognitive outcomes, as well as the motor development and behavioral indicators are not significantly affected by the program.

These results are in line with previous research work that finds mitigating effects of PROGRESA on food consumption (Vicarelli (2011)). The results also complement and contrast to Adhvaryu et al. (2015) who find a mitigating effect of PROGRESA on schooling attainment. We believe the results are not necessarily inconsistent since PROGRESA gives an important financial incentives to keep children in school, even more since the amount of cash transfers increases with grade progression. However, our evidence shows that cognitive development

Table 8: The mitigating effect of Progresa in villages exposed to the rainfall shock. These results are associated to the anthropometric, health, cognitive, motor development adn behavioral indicators collected in 2003. Coefficients are estimated using the randomized experiment and the regression discontinuity approach.

**Cognitive Development Indicators**

| | **Peabody Test** | **Woodcock-Muñoz Test** | | |
|---|---|---|---|---|
| | language | long term memory | short term memory | visual-spatial thinking |
| | (1) | (2) | (3) | (4) |
| Progresa RCT DDD[a] | 0.351*** | -0.123 | 0.029 | -0.020 |
| | (0.1305) | (0.1078) | (0.1564) | (0.1688) |
| RD-DD[b] | -0.103 | 0.084 | 0.654 | 0.004 |
| | (0.3597) | (0.2427) | (0.4521) | (0.3841) |
| Observations | 1993 | 2393 | 2393 | 2393 |

**Anthropometric and Health Indicators**

| | Weight (std) | Height (std) | Stunting | Anemia | Days_sick |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Progresa RCT DDD | 0.340** | 0.189* | -0.173* | -0.190* | -0.170 |
| | (0.1465) | (0.1130) | (0.0956) | (0.0994) | (0.7442) |
| RD-DD | 0.166 | 0.495 | -0.380 | -0.114 | 0.766 |
| | (0.2435) | (0.3525) | (0.3392) | (0.2646) | (1.6931) |
| Observations | 2393 | 2393 | 1642 | 2393 | 2393 |

**Motor Development and Behavioral Indicators**

| | McCarthy | Balance | Depress | Agress |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Progresa RCT DDD | 0.238 | -0.053 | -0.168 | -0.062 |
| | (0.3245) | (0.1250) | (0.2872) | (0.2857) |
| RD-DD | -0.058 | 0.007 | 0.370 | -0.754 |
| | (0.3779) | (0.1452) | (0.6453) | (0.7036) |
| Observations | 2393 | 2392 | 2393 | 2393 |

Controlling for *age* (months), $age^2$, *gender*, *father's language*, and *cohort fixed effects*.
Conley standard errors in parentheses (cutoff= 1 degree). Significant at the * 10%, ** 5%, *** 1% level.
[a] Identification based on the original randomized experiment, interacted with the DiD estimator of the effect of the rain shock on the 1997-2000 cohort. Equation 5 shows the estimation.
[b] Identification based on the discontinuity shown in Figure 4. The discontinuity effect is interacted with the the DiD estimator of the effect of the rain shock on the 1997-2000 cohort. Figures A.8-A.10 shows the rest of the reduced-form estimates on the cohort 1997-2000. Most of the intuition for the effects displayed here are captured by those graphs.

might have only been partially protected with the program. Altogether, this casts important questions about dimensions that could have been more and less protected by conditional cash transfer programs. Either incentives brought by the conditionalities or the cash transfer might protect households and specifically children at critical stages of development. But other dimensions of human capital development might escape the protection given by the program either through mechanisms that are not totally offset or alternative drivers, like stress.[39]

## 6.2 Using a regression discontinuity approach

Here we exploit the administrative rule that determines eligibility to receive PROGRESA, which is based on the household poverty index and a pre-determined cutoff.[40] We take advantage that once the program incorporated beneficiaries, officials would not return to the localities to sign-up more households until after 4-5 years. Therefore, compared to the RCT, the regression discontinuity strategy gives us a larger exposure to the program, starting in 1998 up until 2002. However, as any RD, the treatment effect is locally identified for the households that were at the cutoff point (i.e. the least poor among the eligible).

Adding the regression discontinuity strategy to our difference-in-difference estimation, we build a RD-DD to estimate the potential mitigating effects of PROGRESA as follows:

$$\begin{aligned} Y_{ijt} = \theta_1 \text{ coh97-00}_t + \theta_2 \; rain\_shock_j + \theta_3 \; 1\{x\_pmt_{ij} \geq 0\} + \theta_4 \text{ coh97-00}_t \cdot rain\_shock_j \\ + \theta_5 \; 1\{x\_pmt_{ij} \geq 0\} \cdot \text{coh97-00}_t + \theta_6 \; 1\{x\_pmt_{ij} \geq 0\} \cdot rain\_shock_j + \\ + \theta_7 \; 1\{x\_pmt_{ij} \geq 0\} \cdot \text{coh97-00}_t \cdot rain\_shock_j + f(x\_pmt_{ij}) + \epsilon_{ijt} \end{aligned} \tag{6}$$

where $1\{x\_pmt_{ij} \geq 0\}$ is our PROGRESA treatment variable and $f(x\_pmt_{ij})$ is a polynomial of second degree with different slopes before and after the discontinuity and specified differently for individuals exposed and not exposed to the rain shock. Our parameter of interest is $\theta_7$, which gives the potential mitigating effects of PROGRESA. The main assumption behind the RD strategy is that, other than the treatment benefits, the households around the cutoff

[39] There is a growing literature that gives evidence of negative effects of early-life exposure to stress on later physical health, cognitive abilities, and educational outcomes (Aizer et al. (2015); Eccleston (2011); Kaiser and Sachser (2005); Duncan et al. (2017)).

[40] At the beginning of the program, 41 geographical regions were defined. Regions differ on the weights ($\omega_{jk}$) attributed to the different variables ($X_{ijk}$) and the eligibility cutoff ($\theta_j$) used in the poverty index. A standardized poverty index ($x\_pmt_{ij}$) is calculated as follows:

$$x\_pmt_{ij} = \sum_{k=1}^{K} \omega_{jk} \; X_{ijk} - \theta_j$$

A household $i$ would be eligible for the program if $x\_pmt_{ij} > 0$.

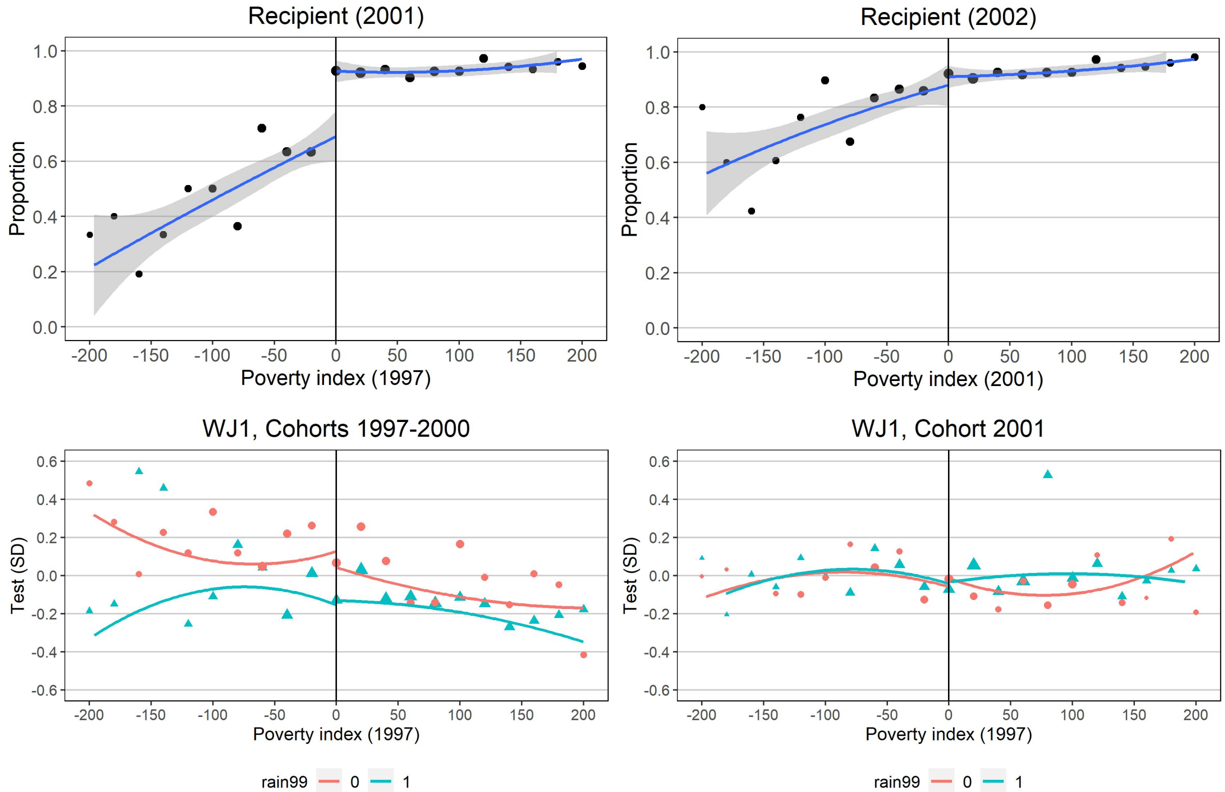
are comparable to each other. Therefore, any discrete change in an outcome variable occurring at the cutoff point can be related to the effect of the treatment (Imbens and Lemieux (2008)).[41]

To show that the identification strategy works, we begin by proving that there is a discontinuity in the likelihood of being a PROGRESA beneficiary at the cutoff. The top two panels in *Figure 4* show that up to 2001 there is a discrete discontinuity exactly at the cutoff level, which reflects an increase in the likelihood of receiving PROGRESA close to 20 percentage points. The discontinuity actually appears since 1998 and persists up to 2002 (*Figure A.7* in the appendix show the evolution of the discontinuity through time). The bottom two panels illustrate how the RD-DD is constructed. The left (right) panel shows the RD estimation for the 1997-2000 (2001) cohort. The red and blue lines correspond to the second-degree polynomial estimations for the localities without and with rain shock present, respectively. The RD-DD would estimate the mitigating effects by looking how the discontinuous presence of PROGRESA might have helped individuals affected by the rain shock to catch-up with the levels of individuals not affected. This effect should be present for the 1997-2000 cohort and not for the 2001 cohort. The example displayed in the bottom two panels corresponds to the long-term memory outcome. As can be seen, the levels of the outcome for individuals affected by the shock tend to be lower for the 1997-2000 cohort, but not for the 2001 cohort. However, the difference in levels, despite being lower with the presence of the program, does not jump for the rain shock group as a mitigation effect would presume. *Figures A.8, A.9* and *A.10* in the appendix show the full set of 1997-2000 cohort graphs for the cognitive, anthropometric, motor and behavioral indicators.

*Table 8* shows the results from the RD analysis for all the outcomes along with the experiment results. No mitigation effects are detected using the RD-DD strategy. Applying the RD analysis to the consumption and diet composition indicators analyzed in this paper, we find positive, but modest effects at the discontinuity. These modest effects are not

[41] To assess the effectiveness of the RD method, the authors estimated the effect of PROGRESA on school attendance in 1999 of children between 6 and 15 years old (the age groups whose attendance is part of the conditionality to receive the monetary benefits). The RD estimates a 5 percentage point, statistically significant, increase in the likelihood of school attendance.

Figure 4: RD-DD design: First Stage and Reduced Forms




This graph is used to illustrate the construction of the RD-DD estimates for the potential compensatory effects that Progresa could have had on the individuals affected by the rain shock.
On each graph, the x-axis corresponds to the standardized poverty index used by the administrative rule to select Progresa beneficiaries. The administrative cutoff is centered at zero. The standardized poverty index is formed with a formula that weights household's asset ownership and socio-economic characteristics of its members.
The top two graphs show the first stage of the discontinuity to show that the identification strategy in fact gives a discontinuous exposure to the program up for 4 years (up to 2001). The y-axis displays the proportion of households that were receiving Progresa based on the poverty index used to assess them in the initial distribution of the program. The top-left graph shows that the discontinuity strategy employed was valid until 2001, while the top-right graph shows that by 2002, such discontinuity disappeared. Figure A.7 in the appendix shows the first stage by year between 1999 and 2002.
The bottom two graphs show the reduced form of the discontinuity for the cohorts employed in the DiD strategy. The left-hand axis shows the result for the 1997-2000 birth cohorts, which corresponds to the cohorts most affected by the rain shock. The right-hand axis shows the results for the 2001 birth cohort, which is used as our control group. In (red) green we display the estimates of individuals in villages (not) affected by the rain shock. The *Woodcock-Muñoz Test 1* (WJ1) is used to assess working and long-term memory. The y-axis displays the level (in SD) of the partialled-out results of the WJ1 test. To partial-out, an OLS estimation of the outcome versus our main set of controls (*age* (months), $age^2$, *gender*, *father's language*, and *cohort fixed effects*) was employed. Each dot in the graph represents a conditional mean using a bin size of 0.1 SDs. The size of each dot is proportional to the number of observations in the bin. Figures A.8 to A.10 in the appendix show the full set of graphs for the outcomes of interest and affected cohorts (1997-2000). Analysis restricted to original randomized treatment villages.

sufficient to counterbalance the negative impact of the rain shock.[42] Although the RD-DD results contrast with the DDD experimental results, they are not inconsistent. By the nature of the RD-DD, the parameters being estimated represent different types of treatment effects.

[42]Graphs can be made available upon request.

Both, the experiment and the RD represent ITT estimates, but in addition the RD is only valid locally. If the treatment has heterogeneous effects through the poverty distribution, larger for the most disadvantaged, the positive effect from the DDD would not necessarily be reflected in the RD-DD estimation.

# 7 Conclusions

Previous work has shown that the early-life conditions tend to have a strong influence on an individual's life. Economists' work has analyzed impacts on income, educational attainment, health, and even mental and physical disabilities (Almond (2006); Almond and Mazumder (2011); Maccini and Yang (2009)). This paper contributes to the literature by estimating the medium-term impact that early-life negative conditions have on specific aspects of children's health and cognitive development. Scores of highly reliable tests (according to U.S. standards) inform about specific abilities that are negatively affected, namely, language, long-term memory, and visual-spatial thinking. Objective anthropometric measures, like height, are also negatively altered. These indicators have been shown to be strong predictors of school and later in life success. Hence, the paper provides information about specific channels that might be driving the long-term effects previously encountered. According this study, income, consumption and diet composition at early life stages are key mechanisms that contribute to produce these results.

Weather shocks related to "El Niño Southern Oscillation" are used to identify negative conditions at early life stages. ENSO is a recurrent climatic event with global impacts that affects hydro-meteorological patterns, causing extreme weather events (e.g. floods, heat waves, droughts). With global warming, extreme weather events are expected to increase in frequency and intensity. Therefore, findings about Mexico are relevant for households in other developing countries with comparable climates, and affected by ENSO-related weather events (e.g. Africa, Latin America, South-East Asia). The analysis of its effects is relevant from an economic, climatic, and public policy perspective.

Finally, some mitigation of PROGRESA against the negative effects of weather shocks has been found. The experimental estimation identified some positive mitigation effects in anthropometric and one of the cognitive outcomes. However, the RD-DD strategy contrasts by not showing any mitigation from the program. In the light of these results, more work is needed to understand the heterogeneity of the impacts to better design policies (or complement existing ones) that could help households protect against harmful shocks that have the characteristic of harming the younger members for their life-long development.

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