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

Arturo Aguilar and Marta Vicarelli*

Abstract

Evidence has shown that shocks in early life have long-term consequences. This paper contributes to our understanding of the channels. Four years after being exposed to exogenous precipitation anomalies during early stages of life, we examine the effects on key developmental indicators. Children affected present lower cognitive development (measured through language, working and long-term memory and visual-spatial thinking) in the magnitude of 0.14 to 0.16 SDs. Lower height, weight and higher anxiety-depression impacts are also identified. Food consumption and diet composition appear to be key drivers behind these impacts. No mitigation from the delivery of conditional cash transfers is found.

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

*Corresponding author – Aguilar, Arturo (ITAM), arturo.aguilar@itam.mx. Vicarelli, Marta (Umass Amherst), mvicarelli@econs.umass.edu. This work was sponsored by the Yale University Climate and Energy Institute, the Harvard University Sustainability Science Program and the Asociación Mexicana de Cultura. We thank Harold Alderman, Doug Almond, Michelle Bell, Larry Katz, Rema Hanna, John Hoddinott, Robert Mendelsohn, and Rohini Pande for their feedback. We are grateful to seminar participants at Banco de Mexico, Columbia University, Ecole Normale Superieure (Ulm-Paris), Ecole Polytechnique (Paris), FEEM-Fondazione Mattei, Georgetown University, Harvard University, IFPRI, IDB, ITAM, LACEA, NEUDC, RAND, Sciences Po (Paris), UMass Amherst and Yale University. Daniel Ramos provided excellent research assistance. All errors are our own.

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)).

This paper investigates 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. With this, we contribute to explain the mechanisms that lead to previously found long-term consequences. We adopt a quasi-experimental design: our identification strategy relies on exogenous extreme weather variations caused by "El Niño Southern Oscillation (ENSO)" during the early stages of an individual's life.

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 translate to results into adulthood.[2] In addition, the longitudinal component of the

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

[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))

dataset allows us to identify possible drivers, through which weather shocks may have affected children's health, development and behavior: 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. 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 developing 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 policies, (iii) we show the impacts that weather and climate extremes might create from a socio-economic perspective, and (iv) we examine the vulnerability reduction potential of conditional cash transfer programs.

To identify negative early-life conditions, we employ extreme precipitation shocks[3] that occurred during the 1998-1999 maize harvest seasons and were related to the ENSO 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)).[4] Using geographical variation in precipitation,[5] we compare

[3]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*.

[4]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)).

[5]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)).

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.[6] 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. Having a shock related to a climatic event like ENSO, gives an additional contribution in the midst of the fact that climatologists suggest that such events are expected to become more frequent and intense (Vecchi and Wittemberg (2010); Cai et al. (2014, 2015)).[7]

The main findings in this paper indicate medium-term negative effects of rainfall shocks on cognitive, behavioral, and anthropometric indicators. On average, children affected between their in-utero development and two years of age exhibit 0.11 standard deviations (SDs) lower weight, 0.14 SDs lower height and higher likelihood of stunting (15.7 percentage points). Language development, working memory, and visual-spatial thinking test scores of these children are 0.14, 0.15, and 0.16 SDs lower than same-aged children not exposed, respectively. These effects are particularly pronounced for children at two years of life when the shock occurred. Children in households exposed to the weather shock present lower results in a behavioral test assessing possible depression-anxiety problems in the order of 0.19 SDs below comparable children not exposed. No strong evidence of negative effects is found for gross motor skills.

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] Total household income, reported two months after the weather extreme event occurred,

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

[7]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*.

[8]In a technical report, it is also mentioned that the occurrence of these shocks severely compromised crop outputs in Mexico (SAGARPA (2007)).

was 19 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 mainly driven by lower revenues from agricultural sources. The year after the event, the monetary value of food consumption (per adult equivalents) was 15 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 (30 percent), as well as in their consumption of fruits and vegetables (15 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.[9] We exploit two sources of exogenous variation to assess this: (i) PROGRESA's randomized distribution during the pilot phase and (ii) a discontinuity in the poverty index used to select eligible households, which remains beyond the pilot phase. The two strategies differ in the duration of their exposure to the PROGRESA benefits. Our analyses do not find any significant evidence of mitigating effects (nor direct effects) of PROGRESA on anthropometric and cognitive outcomes in households exposed to weather extremes. PROGRESA cash transfers do not seem to completely offset the contractions in household consumption and the changes in diet composition in the periods that follow the negative shock.[10]

In a recent paper using PROGRESA's data, Adhvaryu et al. (2015) find that extreme

[9]PROGRESA's pilot program and its randomized evaluation were implemented between 1997 and 2000, which 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, and more specifically its possible role as an insurance mechanism against extreme rainfall shocks events.

[10]Similarly, 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.

rainfall (one SD above or below local average) in the year of birth have negative impacts on children's educational and later employment outcomes.[11] However, they also find that children whose families were randomized to receive PROGRESA experienced a much smaller decline in those educational outcomes. In our paper, we do not find evidence of PROGRESA reducing these effects. We hypothesize that part of the explanation might result from the nature of the outcome indicators: school attendance is one of PROGRESA's conditionalities, making their benefits more salient to parents than investing in early development. If our results and Adhvaryu et al. (2015) are true, PROGRESA would be setting up incentives that fail to accomplish the recommendations set forward by Conti and Heckman (2011), who suggests that the most productive investment is in the earliest years to prevent rather than in latter years to remediate.

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*[12] (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 Niña* (cold event). Each phase typically lasts one year, with a peak in December, and then tapers

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

[12] 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.

down towards a neutral state (Rasmusson and Carpenter (1982)).

ENSO affects hydro-meteorological patterns, causing 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)). In developing countries, weak or absent insurance and credit markets make households employed in weather-sensitive industries (e.g. agriculture and fishing) particularly vulnerable. Its strongest impacts are experienced in countries bordering the Pacific Ocean, from Latin America to Southeast-Asia (Cane et al. (1994)).

ENSO-related changes in weather patterns influence 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)). Changes in climatic patterns and oceanic circulation during ENSO events strongly influence terrestrial and marine ecosystems, and societies around the globe (Holmgren et al. (2001)). *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)). Figure 1 shows the spatial distribution of regional precipitation anomalies, associated to different events. The dark blue areas depict regions affected by abnormally high levels of rain during September-October. As this figure shows, different regions in Mexico are affected in each year at varying levels of intensity.

[Insert Figure 1 about here]

For this study, 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 under a rain-fed system (around 90% of the households). Maize represents the most important crop in Mexico. 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. Maize has two main agricultural seasons: Spring-Summer (78.5% of total production) and Autumn-Winter (21.5%) (SAGARPA (2007)).

In this paper we focus on the Spring-Summer season. The overall season includes 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

[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`

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.

[Insert Table 1 about here]

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 insights 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

[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.).

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 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. Short-term memory is an important first step towards long-term learning of new information. 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, for example, those needed in mathematics (Baddeley et al. (2003); Majerus and Van der Linden (2013)). Short-term memory impairments are usually

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

[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)).

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 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 gathered this information for 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

[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 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)).

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 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 are central to the successful performance of school tasks and were evaluated using a section of the *McCarthy Scale of Children's Abilities* (MSCA) (McCarthy (1972)). The MSCA provides an assessment of gross motors skills, focusing on leg coordination for children between 2 and 6. Children are required to complete multiple exercises and the results are combined into a single *McCarthy indicator*.[20] Besides school failure, difficulty or inability to perform the actions assessed can be debilitating for young adults in rural areas and 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)).

[20]Exercises include: (i) standing on one foot to measure the ability to perform the task and the amount of time endured, (ii) walking forward in a straight line, (iii) walking backward, (iv) tip-toeing, and (v) jumping rythmically.

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. Behaviors are assessed through statements, such as "The child cries a lot", "The child is talkative", "The child is anxious", etc. Answers are then combined to build behavioral indicators. Child psychology literature suggests that early identification of behavioral and emotional problems in infancy and among preschoolers is critical for several reasons: first, behavioral and emotional problems in early childhood have been shown to be stable over time; second, young children with recurrent and co-morbid externalizing and internalizing problems have the most impairment as they grow; and lastly, early detection of behavioral and emotional problems has been shown to lead to successful early intervention efforts to ameliorate these problems (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 behav-

[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)).

ioral assessments like the one described here, 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 1998 and 2000.

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.

In the estimations, a binary variable for the ENSO-related rainfall shock ($rain\_shock$) is used to analyze the impact of negative conditions during early stages of life on children's outcomes. The decision to use a binary variable for the rain shocks was motivated by two main reasons: (i) the qualitative evidence found on weather reports 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; and (ii) the use of the binary variable aids the ease of interpretation of the results. Nonetheless, in our analysis we also investigate a non-parametric flexible relation.

The rain shock variable was constructed using each grid's *standardized precipitation anomaly*, which is calculated for each grid-month pair as the difference with respect to the long-term mean (calculated over the period 1961-1999) in terms of 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 local climatology (i.e. 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 abnormal conditions with respect to usual local levels of precipitation. 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 and Steinberg (2017)).

It is important to emphasize that in Mexico precipitation patterns during *El Niño* and *La Niña* events do not repeat themselves in a consistent way at the local level. On the contrary, as shown in *Figure 1*, the spatial distribution of extreme precipitation changes from one event to the next in a rather unpredictable way.

[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`

Figure 2 shows the monthly distribution of the *standardized precipitation anomaly* for the Spring-Summer agricultural seasons related to the 1998 *El Niño* and 1999 *La Niña* events.[24] For our main analysis, 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 at the harvest season, which was preceded by normal rainfall levels during the planting time.[25] 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.

[Insert Figure 2 about here]

Using the *standardized precipitation anomaly* we create the binary variable *rainfall shock*. A rainfall shock is identified ($rain\_shock = 1$) whenever the *standardized precipitation anomaly* is above 0.7 standard deviations in September or October of 1999 (harvest months).[26] *Figure 3* shows the geographical distribution of the 1999 rain shock in the 259 localities included in the dataset.[27] We perform sensitivity analyses testing other cutoff points (0.5 and 1 SDs) and provide a non-parametric relation of our outcomes with respect to different levels of standardized precipitation anomalies as well.

[Insert Figure 3 about here]

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

[25] We also provide a comparison by using 1998 to show that it is not something particular of this year.

[26] 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*.

[27] Similarly, *Figure A.1* 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. Therefore, the key variables in the specifications 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. The main specification to be estimated is:

$$Y_{ijt} = \eta_t + \gamma_1 \text{ coh97-00}_t \cdot rain\_shock_j + \gamma_2 \text{ coh01}_t \cdot rain\_shock_j + \beta\ X_{ijt} + \epsilon_{ijt} \qquad (1)$$

where Y_{ijt} is the outcome for individual i in pixel j born in year t; eta_t accounts for cohort fixed effects; coh97-00$_t$ indicates if the individual was born in years 1997 to 2000 and coh01$_t$ indicates if he was born in 2001; $rain\_shock_j$ is the location variable and corresponds to a dummy indicating if a weather shock occurred in 1999 at pixel j;[28] X_{ijt} are controls for individual i in pixel j.

To explore the heterogeneity with respect to the timing variable we also estimate:

$$Y_{ijt} = \eta_t + \left(\sum_{k=1997}^{2001} \gamma_k\ coh\_k_t \cdot rain\_shock_j \right) + \beta\ X_{ijt} + \epsilon_{ijt} \qquad (2)$$

where coh_k_t is a dummy variable indicating if the individual was born in year k.

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 analysis considers children born between 1997 and 2001, for which we have the richest set of indicators available. Given that the rain shock used for the estimations took place in 1999, the parameters of interest (γ_1 and γ_k) will indicate 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, γ_1 in equation (1) captures the difference between exposed and not exposed individuals during their in-utero development or first years

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

of life. Similarly, in equation (2), γ_{1997} will give the effect of the shock on children that were one to two years old at the time of the shock with respect to same-aged children not affected. As for γ_2 in equation (2) and γ_{2001} in equation (2), they show the difference between locations affected and not affected by the shock for children born one to two years after the occurrence of the shock. These children are closer to not being affected by the shock unless the effects were more persistent, thus we use them as potential controls.

The main estimates include clustered (at the grid-cell level) and Conley spatially-correlated standard errors with 1 decimal degree cutoff (Conley (1999)). Sensitivity analyses for the Conley standard errors using a distance threshold of 2 decimal degrees are presented in *Table A.1*.

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.[29] *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 the baseline, for most observable 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[30] 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 in our empirical specification the indicators from Table 2 as additional control variables; results of the robustness checks are discussed in Section 4.

[Insert Table 2 about here]

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

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

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)).[31]

Table 3 reports the estimated effects of excessive rainfall shocks during the 1999 harvest season on cognitive outcomes.[32] The estimates suggest negative and significant effects of the rainfall shocks on language development (equal to 0.14 SDs on average), long-term and working memory (0.15 SDs), and visual-spatial thinking abilities (0.16 SDs). 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 0.60, 0.31, and 0.29 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 0.19, 0.21, and 0.21 SDs lower than scores for same aged-children not affected by the shock. Children who were exposed to the

[31] 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)).

[32] For ease of interpretation we standardized the test scores.

shock close to their birth or during their in-utero development (i.e. born in 1999 and 2000) exhibit smaller, but mostly non-significant effects. Also, children from the affected regions that were born two years after the shock are very similar in every measure to same-aged children in non-affected areas.

[Insert Table 3 about here]

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 occurring during the 1999 harvest season 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).

[Insert Table 4 about here]

Results show significant lower weight and height for children that were exposed in-utero or during the first two years of life to the shock. On average, exposed children exhibit 0.11 and 0.14 standard deviations (SDs) lower weight and height with respect to same-aged children not exposed. The stronger effects are shown in children that were between one and two years at the time of the shock. In particular, the shock had effects in the affected individual's height, irrespective of his stage of development. The negative effects in height range from $0.18-0.20$ SDs if the shock occurred during the children's first two years of life to $0.10-0.11$ if the shock occurred during their in-utero development or just after birth. The negative impacts on height are substantive enough to significantly increase the probability of stunting. On average, affected children have a 15.7 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 development.[33] The negative impact on weight for children aged two and one at the time of the shock is 0.25 SDs and 0.15 SDs, respectively. There seems to be no significant effect for children in-utero at the time of the shock.

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.

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)). In *Table 5*, we show the result from analyzing the possible relation between weather shocks and motor skills in children exposed to the shocks. No statistically significant effects are found using the aggregated MSCA index. We also analyze the possible effect of weather extremes on each component of the MSCA indicator. Table A.2 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.

[Insert Table 5 about here]

4.4 Effects on behavioral indicators

Table 5 shows the results when using the two CBCL indicators described in *section 2*. The *anxiety and depression* index displays an important effect (0.19 SDs) with respect to same-

[33] 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.

aged children not affected by the shock. In contrast, the *aggressive behavior* index does not display significant effects. The negative effect on anxiety and depression is more heavily concentrated for children that were in-utero stage at the time of the shock (0.27 SDs for children born in 2000).

Tables A.3 and A.4 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 two questions most influenced by the 1999 shock towards the *anxiety and depression* index results are: (i) "*does your child feel nervous often?*" and (ii) "*does your child feel the need to be perfect?*". In total, six out of nine questions that form the index, display significant differences (all at the 1% level) between children exposed and not exposed to the shock.

Despite the fact that the aggregate *aggressive behavior index* did not display any significant difference between children exposed and not exposed to the weather shock, answers to some questions used to build the index display significant effects when analyzed individually: (i) *does your destroys his / her things?*, (ii) *does she/he demands a lot of attention?*, and (iii) *does she/he gets into fights often?*. Questions (i) and (iii) are the most closely related to physical aggression among the questions of the aggression index. This suggests that null effects towards aggression should probably not be disregarded.

These behavioral indicators outcomes may suggest that weather shocks have 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 functions (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)).

4.5 Robustness checks

4.5.1 Testing sensitivity to the 0.7 cutoff value for the rain shock

The *rain shock* variable employed in the main specifications is equal to 1 if the standardized precipitation anomaly in a given gridcell is above 0.7 (i.e. standard deviations from the long-term mean). When *rain shock* is equal to 1 the corresponding geographical location is affected by an excessive rainfall shock. To verify that our results are not particular of the 0.7 threshold point, we replicate the analysis using different threshold points: 0.5 and 0.9. The results are consistent across different threshold points

The idea is that since the crop has already developed at this stage, there is a negative relation between positive *rain anomalies* and crop outcomes since harvesting is more difficult during rains, particularly in the extreme levels of rain, which usually develop into floods. This negative relation translates into poorer development and health outcomes that could result from higher values of *rain anomalies*. Given our identification strategy, the rain anomaly variation is assumed to be exogenous, thus causality is established.

Figure 4 shows four graphs that contain the main results of the paper. As expected, a negative relation is found between *rain anomalies* and developmental outcomes. For instance, height, language development and anxiety-depression outcomes are negatively related with *rain anomalies*.[34] Figures A.2 to A.4 in the appendix display the rest of the outcomes analyzed. Interestingly, short-term memory and gross motor skills, variables that did not show any significant effect in our main regression model, here appear to be negatively related to *rain anomalies*. As we mentioned previously, these outcomes are related to more extreme cases; a lack of precision and the effects being more rare might explain the lack of statistical significance in the regression analysis presented above. Finally, the lack of effect is confirmed for outcomes like anaemia and aggressive behavior.

[Insert Figure 4 about here]

4.5.2 Sensitivity to the geographical identification strategy

As discussed in *Section 3*, the empirical specification is based on the assumption that the rain shock is exogenous. Since the definition of the rain shock is geographical, such is the variation being employed in this paper. As detailed above, the correlation between close-by locations results on affected and non-affected localities being clustered. This is made evident in Figures 3 and A.1, which show the geographical distribution of the shocks. A concern of

[34] The *anxiety and depression index* appears to be positively related, but it should be remembered that a positive number in the depression index represents a higher level of anxiety-depression.

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. To test for this, we redo 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.5 shows the regions being removed for these tests and the remaining localities being used in the specifications.

Tables A.5 to A.10 in the appendix summarize the results from this test. Results calculated in these tables are consistent with our main result: the children that were on early stages of their life at the time of the shock were the most affected. Also, Figure 1 in the appendix confirms that the standardized precipitation anomaly measure tends to be clustered geographically, but in previous occurrences of ENSO, it has hit different regions. This supports our geographical exogenous variation assumption.

4.5.3 Using the 1998 rain shock

Figure A.1 shows the geographical distribution of the shock in 1998 identified also using a 0.7 cutoff. An important overlap exists with respect to the use of the 1999 shock. Tables A.11, A.12 and A.13 show the results using the 1998 rain shock occurrence. Panel A presents the baseline results using the 1999 shock, panel B shows the result of the specification from equation (1), but with the 1998 shock. Finally, panel C shows the result of having the shock in both 1998 and 1999. As can be seen from the tables, the effects are very similar through the different cases.

4.5.4 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 regional effects, it is likely that these additional control variables will pick up some of that effect, thus altering the main coefficients. *Tables A.14, A.15,* and *A.16* show that the main estimates do not change significantly when these additional controls are added and thus provide reassuring evidence for our main claim.

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 intermediate mechanisms. As in the previous analysis, the underlying assumption for the identification is the exogeneity of the shock. *Tables 6* and *7* show the main results of the mechanisms analysis. In the appendix, *Tables A.17* and *A.18* replicate these results using rainfall shocks that occurred in 1998.

$$Y_{ijt} = \gamma_0 + \gamma_1 \ rain\_shock_j + \beta X_{ij} + \epsilon_{ijt} \tag{3}$$

Income In response to shocks, households may experience income reductions with possible consequent contractions in consumption. We estimate the effect of rainfall shocks on total household income and income from agricultural activities measured in the year of the shock (period t) and up to two years after the shock (at periods $t+1$ and $t+2$). The estimates indicate that households exposed to the shock have lower total income than those not affected, being the effect persistent over three periods t, $t+1$, $t+2$. The results shown in *Table 6* indicate a lower income ranging between 19% and 34%. This reduction is primarily driven by lower agricultural income, a reduction that ranges between 22% 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.

[Insert Table 6 about here]

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. 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 and neighbors immediately after the shock in the order of 1.4 and 1.5 percentage points, respectively. 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), may lead 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 at periods t, $t+1$ and $t+2$. Results in *Table 7* show contractions in the value of food consumption over the three periods that range between 6% (non-significant) and 15% (p-value=0.029).[35] These estimates confirm the results found by Vicarelli (2011).

[Insert Table 7 about here]

[35] *Table A.18* in the appendix shows that these results are consistent for the 1998 shock and that the value of food consumption lasts up to two years after the shock.

A reduction in the monetary value of food consumption is likely to lead to a dietary shift towards cheaper foods. As expected, three main changes in diet composition are also found in households exposed to the shock, compared to households not exposed. First, consumption of tortillas[36] increased immediately after the shock by 9%, 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 in periods t to $t + 2$ by 20% to 30%. Lastly, consumption of fruit and vegetables decreased by 15% in period $t + 1$ using the 1999 shock results.

This 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 negative consequences on the health conditions, brain development and overall development of young children (Walker et al. (2007, 2011); Morgane et al. (1993)). Interestingly, this substitution led to non-significant changes in overall food consumption if measured by total quantities (kg) or calories.

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 (period t) and up to two years 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 43% in period t. Nonetheless, it is possible that medicine expenditure are driven by liquidity constraints rather than changes in health status.

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

6 The Role of Progresa

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, with follow-up surveys in 2003 and 2007 to assess its short and medium-term benefits (Skoufias (2001); Behrman et al. (2005)). Eligibility for the program was determined based on this index and a pre-determined threshold.[37] 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 rainfall shock for households eligible to receive PROGRESA.

6.1 Empirical identification of PROGRESA's effects

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. The first empirical estimation used here to assess the potential mitigating effects of PROGRESA follows the line of randomized control trial's estimations:

$$Y_j = \eta_1 \; rain\_shock_j + \eta_2 \; Treat_j + \eta_3 \; rain\_shock_j * Treat_j + \epsilon_j \tag{4}$$

where Y_j represents the outcomes (cognitive, anthropometric, or behavioral) aggregated at the village level; $rain_j$ represents the dummy variable indicating the occurrence of the rainfall shocks; and $Treat_j$ indicates if village j was randomly selected as a treatment locality.

Here, η_2 represents the effect of the treatment on the outcomes at villages not exposed to rain shocks, and $\eta_2 + \eta_3$ represents the effect of the treatment in villages affected by the

[37] 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.

shocks. In this estimation, it is important to keep in mind that the control villages were added to the program in 2000, less than two years after the treatment villages. Given that the outcomes are measured in 2003, the randomization makes possible to identify early versus late treatment effects, rather than the more traditional treatment versus control effect.

Regression Discontinuity (RD) In this part, we take advantage of the administrative rule that determines eligibility based on the household poverty index and a pre-determined cutoff. At the beginning of the program, 41 geographical regions were defined. Regions differ from each other on the weights attributed to the different variables used to generate the poverty index, and the cutoff value to select beneficiaries. A standardized poverty index (x_pmt_{ij}) is formed by subtracting the regional cutoff to the each household's poverty index.[38] Therefore, independently of the region, a household would be eligible for the program if its standardized poverty index is above zero ($x\_pmt_{ij} > 0$). The equation that estimates the potential mitigating effects of PROGRESA would be:

$$\begin{aligned} Y_j = \theta_1 \; rain\_shock_j + \theta_2 \; 1\{x\_pmt_{ij} \geq 0\} + \theta_3 \; rain\_shock_j * 1\{x\_pmt_{ij} \geq 0\} + \ldots \\ + f(x\_pmt_{ij}) + \epsilon_j \end{aligned} \quad (5)$$

The main assumption behind the RD strategy is that, other than the treatment benefits, the households around the cutoff 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)).[39]

[38] The formula employed to calculate x_pmt_{ij} is the following:

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

where ω_{jk} is the weight of variable k, which is specific to region j, X_{ijk} is the variable k of household i in region j and θ_j is the regional cutoff.

[39] 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 at the cutoff for those children in treatment villages. No discrete change is observed for children in control villages. Furthermore, after the cutoff, the level of school attendance for control and treatment villages follows different trends (graph available upon request).

We organized the RD analysis in two parts: first, we show that there is a discontinuity in the likelihood of being a PROGRESA beneficiary at the administrative cutoff; then, we analyze the conditional means of the outcome variables around the poverty index cutoff. By estimating equation (5) we are able to estimate any potential positive impact of the program without being affected by a rain shock (θ_2) and the potential mitigating effect that the program might produce (θ_3).

6.2 Results on the potential mitigation effects of PROGRESA

Randomized Experiment *Table 8* presents the intent to treat (ITT) estimates of PROGRESA differencing between villages that suffered a weather shock and those that did not. The evidence from the tables suggests that there is neither a mitigation nor a direct effect from PROGRESA on the anthropometric and cognitive outcomes analyzed in this paper. To produce this analysis, data was aggregated at the village level given that both, the randomization and the identification of the weather shocks, were at the village level.

[Insert Table 8 about here]

In previous work, Fernald and Gertler (2004) find no differences between children in the original treatment and control villages. They argue that children in the original control villages catch-up with children that received the benefits earlier. In addition to using the randomized experiment, next we show the results of exploiting the rule that determines household eligibility and the discontinuity formed, which remains from 1998 to 2002.

Regression Discontinuity *Figure 5* shows the first stage results described in *Section 6.1*, which justify using of RD to identify the effects of PROGRESA. These graphs show the evolution of the likelihood to be a PROGRESA beneficiary, conditional on the standardized poverty index (x_pmt). As expected form the program's rules, there is a discrete discontinuity exactly at the cutoff level, equal to 46.5 percentage points (according to a parametric estimate). The discontinuity persists and does no change much until 2002. Between late 2001 and early 2002, the program was expanded and the models to estimate the poverty index changed, thus explaining discontinuity disappearing in 2002.

[Insert Figure 5 about here]

The analysis is restricted to treatment localities. If control localities were added, the shape of the graphs in *Figure 5* would change in early 2000, when the control villages began to receive PROGRESA's benefits. By restricting the analysis to treatment villages, we have a discontinuity that remains close to constant until 2002. Therefore, the RD estimates give the difference between receiving the treatment starting on 1998 versus 2002 at the discontinuity. This approach gives a lower time frame for households that receive the benefits later to catch-up.

Table 9 shows the results from the RD analysis for all the outcomes in a similar fashion to the experiment results. Consistent with the experiment results, no mitigation from PROGRESA is detected. *Figures A.6* to *A.8* graphically show the regression discontinuity results for the main outcomes. The difference in the level of the means for the two subgroups reflects the negative effect of the shock, which is consistent with the analysis shown in *Section 4*. However, PROGRESA does not seem to provide mitigation effects against the shocks, nor even direct effects on the outcomes.

[Insert Table 9 about here]

The results are surprising given that previous research has shown positive effects of PROGRESA on food consumption and diet composition (Behrman and Hoddinott (1999); Hoddinott et al. (2000); Vicarelli (2011)). Applying the RD analysis to the consumption and diet composition indicators analyzed in this paper, we find positive, but modest effects at the discontinuity. However, the positive changes on these indicators do not allow for a mitigation of the negative effects of the rain shocks.[40] A possible explanation could be related to intra-household allocation of resources. Previous work has shown that when facing negative weather income shocks, children are the most affected in terms of consumption. Baez and Santos (2007) give evidence that after hurricane Mitch hit Nicaragua, children's likelihood of being undernourished significantly increased, while adult's consumption wasn't reported to be greatly affected. In the case of PROGRESA there is also a higher incentive to

[40] Graphs can be made available upon request.

protect children at school age, given that the amount of cash transfers significantly increases with school attendance of 8 to 15 year old children (i.e. children attending 3rd to 6th grade of primary or lower secondary). Finally, the negative conditions that result from the exposure to weather shocks might have led to stress. 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)).

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, no mitigation of PROGRESA against the negative effects of weather shocks has been found. Some potential reasons are: (i) PROGRESA did not completely mitigate the negative effects of the weather shocks on consumption and diet composition; (ii) intra-household imbalance in the distribution of PROGRESA's resources; (iii) other components related to the weather shocks, like stress, might be contributing to the results and are not offset by PROGRESA. In future work, we plan to assess the second point to determine if intra-household allocation of resources could explain the no-effect result found for PROGRESA in this and previous studies (Fernald and Gertler (2004)). Heterogeneity in the effects of PROGRESA with respect to children's initial malnutrition is also on our agenda.

References

Achenbach, Thomas M., and Leslie Rescorla. 2001. "ASEBA school-age forms and profiles: and integrated system of multi-informant assessment." ASEBA. Burlington VT.

Adams, R.M., Chen, C.C., McCarl, B.A. and Weiher, R.F., 1999. The economic consequences of ENSO events for agriculture. *Climate Research*, 13(3), pp.165-172.

Adhvaryu, Achyuta, Teresa Molina, Anant Nyshadham, and Jorge Tamayo, 2015. Helping children catch up: Early life shocks and the progresa experiment. Mimeo.

Amendola, R., Castillo, E., and Martinez, P. A. 2005. Forage resource profiles. Mexico. FAO editor. Country Pasture Profiles. Rome, Italy. On CD.

American Educational Research Association, American Psychological Association, & National Council on Measurement in Education (1999). *Standards for educational and psychological testing* Washington, D.C.: American Educational Research Association.

Aizer, Anna, Laura Stroud, and Stephen Buka. 2015. Maternal stress and child outcomes: evidence from siblings. *Journal of Human Resources* 51 (3): 523-555.

Alderman, Harold, John Hoddinott, and Bill Kinsey. 2006. Long term consequences of early childhood malnutrition. *Oxford Economic Papers, Oxford University Press* 58 (3): 450-474.

Allan, R. 2000. ENSO and Climatic Variability in the Past 150 years. In *El Niño and the Southern Oscillation, Multiscale Variability and Global and Regional Impacts*, edited by Vera Markgraf and Henry Diaz. Cambridge, MA: Cambridge University Press.

Allan, Richard. P., and Brian J. Soden. 2008. Atmospheric warming and the amplification of precipitation extremes. *Science* 5895 (321): 1481-1484.

Alderman, Harold, John Hoddinott, and Bill Kinsey. "Long term consequences of early childhood malnutrition." Oxford economic papers 58.3 (2006): 450-474.

Almond, Douglas. 2006. Is the 1918 influenza pandemic over? Long-term effects of in utero influenza exposure in the post-1940 U.S. population. *Journal of Political Economy* 114 (4): 672-712.

Almond, Douglas and Bhashkar Mazumder. 2011. Health capital and the prenatal environment: the effect of Ramadan observance during pregnancy. *American Economic Journal: Applied Economics* 3 (4): 56-85.

Attanasio, O. P., Fernández, C., Fitzsimons, E. O., Grantham-McGregor, S. M., Meghir, C.,and Rubio-Codina, M. (2014). Using the infrastructure of a conditional cash transfer program to deliver a scalable integrated early child development program in Colombia: cluster randomized controlled trial. *BMJ* 349: g5785.

Aylward, G. P. (2005). Neurodevelopmental outcomes of infants born prematurely. Journal of Developmental and Behavioral Pediatrics, 26(6), 427-440.

Baddeley, A. (2000). The episodic buffer: a new component of working memory? Trends in cognitive sciences, 4(11), 417-423.

Baddeley, A. D., Kopelman, M. D., and Wilson, B. A. (Eds.). (2003). *The handbook of memory disorders*. John Wiley and Sons.

Baez, Javier, and Indhira Santos. 2007. Children's vulnerability to weather shocks: a natural disaster as a natural experiment. Techincal Report. World Bank.

Bagner, D. M., Rodriguez, G. M., Blake, C. A., Linares, D., and Carter, A. S. (2012). Assessment of behavioral and emotional problems in infancy: A systematic review. Clinical child and family psychology review, 15(2), 113-128.

Barber, Richard, and Francisco P. Chavez. 1983. Biological consequences of El Niño. *Science* 222: 1203-1210.

Barham, Tania. "The Effects of Child Health Interventions on Later Life Cognitive Functioning: Evidence from Matlab in Bangladesh." *American Economic Journal: Applied Economics* 4, no. 1 (2012): 245-73.

Barker, David J.P. 1998. *Mothers, Babies and Health in Later Life.* Edinburgh, UK: Churchill Livingstone.

Barker, David JP. "In utero programming of chronic disease." Clinical science 95, no. 2 (1998): 115-128.

Bateson, Patrick, David Barker, Timothy Clutton-Brock, and Debal Deb. "Developmental plasticity and human health." Nature 430, no. 6998 (2004): 419.

Behrman, Jere, and John Hoddinott. 1999. Program evaluation with unobserved heterogeneity and selective implementation: the Mexican Progresa impact on child nutrition. *Oxford Bulletin of Economics and Statistics* 67: 547-569.

Behrman, Jere, and Petra Todd. 2000. Aleatoriedad en las muestras experimentales del Programa de Educación, Salud y Alimentación (PROGRESA). In *Evaluación de Resultados del Programa de Educación, Salud y Alimentación*. Mexico City: SEDESOL.

Behrman, Jere., Piyali Sengupta, and Petra Todd. 2005. Progressing through PROGRESA: an impact assessment of Mexico's School Subsidy Experiment. *Economic Development and Cultural Change* 54 (1): 237-275.

Bellisle, France. "Effects of diet on behaviour and cognition in children." British Journal of Nutrition 92, no. S2 (2004): S227-S232.

Birch, E. E., Garfield, S., Hoffman, D. R., Uauy, R., and Birch, D. G. (2000). A randomized controlled trial of early dietary supply of long-chain polyunsaturated fatty acids and mental development in term infants. Developmental medicine and child neurology, 42(3), 174-181.

Buser, Thomas, Hessel Oosterbeek, Erik Plug, Juan Ponce, and Josh Rosero. 2014. The impact of positive and negative income changes on the height and weight of young children. IZA Discussion paper No. 8130.

Cai, W., Borlace, S., Lengaigne, M., Van Rensch, P., Collins, M., Vecchi, G., Timmermann, A., Santoso, A., McPhaden, M.J., Wu, L. and England, M.H., 2014. Increasing frequency of extreme El Niño events due to greenhouse warming." *Nature Climate Change* 4(2): 111-116.

Cai, Wenju, Agus Santoso, Guojian Wang, Sang-Wook Yeh, Soon-Il An, Kim M. Cobb, Mat Collins et al. 2015. ENSO and greenhouse warming. *Nature Climate Change* 5, no. 9: 849-859.

Cane, Mark A., Gidon Eshel, and R.W. Buckland. 1994. Forecasting Zimbabwean maize yield using eastern equatorial Pacific sea surface temperature. *Nature* 370: 204–205.

Case, Anne, and Christina Paxson. 2008. Stature and status: height, ability, and labor market outcomes. *Journal of Political Economy* 116 (3): 499-532.

Chan, J. C. L. 2000. Tropical cyclone activity over the western North Pacific associated with El Niño and La Niña events. *journal of Climate*. 13: 2960-2972.

Coady, David. 2000. *Final Report: The Application of Social Cost-Benefit Analysis to the Evaluation of PROGRESA*. Washington, DC: International Food Policy Research Institute. IFPRI.

Conde, Cecilia, Rosamaria Ferrer, Raquel Arajuo, Carlos gay, Victor Magaña Jose Luis Perez, Tomas Morales, Saturnino Orozco. 2004. El Niño y la Agricultura. In *Los Impactos del Niño en México*, edited by Victor Magaña. Mexico City: U.N.A.M.

Conley, Timothy G. 1999. GMM estimation with cross sectional dependence. *Journal of Econometrics* 92 (1): 1-45.

Conti, G. and James J. Heckman. 2014. Economics of Child Well-Being. In Ben-Arieh, A. et al., eds. *"Handbook of Child Well-Being: Theories, Methods and Policies in Global Perspective.* Springer Publishing Company, pp. 363-401

Currie, J. and Vogl, T., 2013. Early-life health and adult circumstance in developing countries. *Annu. Rev. Econ.*, 5(1), pp.1-36.

Currie, Janet and Maya Rossin-Slater, 2034. Hurricanes and Birth Outcomes. *Journal of Health Economics.*, 32(3), pp.487-503.

Davis, A. S., and D'Amato, R. C. (Eds.). (2010). Handbook of pediatric neuropsychology. Springer Publishing Company.

Dell, Melissa, Benjamin F. Jones and Benjamin A. Olken. 2009. Temperature and income: reconciling new cross-sectional and panel estimates. *American Economic Review: Papers & Proceedings* 99 (2): 198-204.

Deschênes, Olivier, and Michael Greenstone. 2006. The economic impacts of climate change: evidence from agricultural profits and random fluctuations in weather. Research Paper no. 04-26. Department of Economics, MIT, Cambridge.

Donat, Markus G., Andrew L. Lowry, Lisa V. Alexander, Paul A. O'Gorman, and Nicola Maher. "More extreme precipitation in the world's dry and wet regions." Nature Climate Change 6, no. 5 (2016): 508-513.

Duncan, B., Hani Mansour and Daniel Rees. 2017. It's just a game: the Super Bowl and low birth weight. *Journal of Human Resources* 52 (4): 946-978.

Duncan, Greg et al. 2007. School Readiness and Later Achievement. *Developmental Psychology* 43 (6): 1428-1446.

Dunn, L.M., and D.M. Dunn1981. Manual for the Peabody Picture Vocabulary Test - Revised. Circle Pines, MN: American Guidance Service.

Eccleston, Melissa. 2011. In Utero Exposure to Maternal Stress: Effects of 9/11 on Birth and Early Schooling Outcomes in New York City. Working Paper Harvard University 2011.

Fafchamps, Marcel, Christopher Udry, and Katherine Czukas. 1998. Drought and saving in West Africa: are livestock a buffer stock? *Journal of Development Economics* 55 (2): 273-305.

Fernald, Lia, and Paul J. Gertler. 2004. The medium term impact of Oportunidades on child development in rural areas. Final Report. SEDESOL, Mexico City.

Fernald, Lia CH, Paul J. Gertler, and Lynnette M. Neufeld. "Role of cash in conditional cash transfer programmes for child health, growth, and development: an analysis of Mexico's Oportunidades." The Lancet 371.9615 (2008): 828-837.

Fernald, Lia CH, Paul J. Gertler, and Lynnette M. Neufeld. 2009. 10-year effect of Oportunidades, Mexico's conditional cash transfer programme, on child growth, cognition, language, and behaviour: a longitudinal follow-up study. *The Lancet* 374, no. 9706 (2009): 1997-2005.

Galler, J., Bryce, C., Waber, D., Hock, R., Exner, N., Eaglesfield, D., Harrison, R. (2010). Early Childhood Malnutrition Predicts Depressive Symptoms at Ages 11?17. Journal of Child Psychology and Psychiatry, and Allied Disciplines, 51(7), 789?798.

Geary, D. C. (1993). Mathematical disabilities: cognitive, neuropsychological, and genetic components. Psychological bulletin, 114(2), 345-362.

Geary, D. C. (2004). Mathematics and learning disabilities. Journal of learning disabilities, 37(1), 4-15.

Georgieff, M. K. (2007). Nutrition and the developing brain: nutrient priorities and measurement. The American journal of clinical nutrition, 85(2), 614-620.

Gertler PJ, Heckman JJ, Zanolini A, Pinto R, Zanolini A, Vermeersch C, et al. 2014. Labor market returns to an early childhood stimulation intervention in Jamaica. Science. 344: 998-1001.

Gine, Xavier, Lev Menand, Robert Townsend, and James Vickery. 2008. Microinsurance: a case study of the Indian Rainfall Index Insurance Market. Policy Research Working Paper Series no. 5459. World Bank, Washington DC.

Gluckman, Peter D., Mark A. Hanson, Cyrus Cooper, and Kent L. Thornburg. "Effect of in utero and early-life conditions on adult health and disease." New England Journal of Medicine 359, no. 1 (2008): 61-73.

Gray, William M. 1984. Atlantic seasonal hurricane frequency. Part I: El Niño and 30 mb quasi-biennial oscillation influences. *Monthly Weather Review* 112: 1649-1668.

Grantham-McGregor, Sally, Yin Bun Cheung, Santiago Cueto, Paul Glewwe, Linda Richter, and Barbara Strupp. 2007. Developmental potential in the first 5 years for children in developing countries *The Lancet* 369: 9555, 60-70.

Hegarty, M., and Kozhevnikov, M. (1999). Types of visual-spatial representations and mathematical problem solving. Journal of educational psychology, 91(4), 684-689.

Heim, Richard. 2002. A review of twentieth-century drought indices used in the United States. *Bulletin of the American Meteorological Society* 84: 1149-1165.

Hoddinot, John, Emmanuel Skoufias, and Ryan Washburn. 2000. *The Impact of Mexico's Programa de Educación, Salud y Alimentación on Consumption.* Washington DC: International Food Policy Research Institute. IFPRI.

Hoddinott, John, and Bill Kinsey. "Child growth in the time of drought." Oxford Bulletin of Economics and statistics 63.4 (2001): 409-436.

Hoddinott J, J.A. Maluccio, J.R. Behrman, R. Flores, R. Martorell. 2008. Effect of a nutrition intervention during early childhood on economic productivity in Guatemalan adults. Lancet. 371:411-6.

Holmgren, Milena, Marten Scheffer, Exequiel Ezcurra, Julio R. Gutierrez, Godefridus M.J. Mohren. 2001. El Niño effects on the dynamics of terrestrial ecosystems. *Trends in Ecology and Evolution* 16 (2): 89-94.

Joseph, Laurice, M. 2011 Encyclopedia of Child Behavior and Development pp. 1095-1097. Sam Goldstein and Jack Naglieri (Eds.) Springer, US.

Imbens, Guido, and Thomas Lemieux. 2008. Regression discontinuity designs: a guide to practice. *Journal of Econometrics* 142 (2): 615-635.

Isaacs, Elizabeth B., Alan Lucas, Wui K. Chong, Stephen J. Wood, Cheryl L. Johnson, Clare Marshall, Faraneh Vargha-Khadem, and David G. Gadian. "Hippocampal volume and everyday memory in children of very low birth weight." Pediatric research 47, no. 6 (2000): 713-720.

Kaiser, Sylvia, and Norbert Sachser. 2005. The Effects of Prenatal Social Stress on Behaviour: Mechanisms and Function. *Neuroscience and Biobehavioral Reviews* 29: 283-294.

Keyantash John, and John Dracup. 2004. An aggregate drought index: assessing drought severity based on fluctuations in the hydrological cycle and surface water storage. *Water Resources Research* 40(9): W09304.

Larkin, Narasimhan, and D. E. Harrison. 2001. ENSO warm (El Niño) and cold (La Niña) event life cycles: ocean surface anomaly patterns, their symmetries, asymmetries, and implications. *Journal of Climate* 15: 1118-1140.

Larkin, Narasimhan, and D. E. Harrison. 2005. Global seasonal temperature and precipitation anomalies during El Niño autumn and winter. *Journal of Geophysical Research Letters* 32: L16705.

Leight, J., Glewwe, P. and Park, A., 2015. The Impact of Early Childhood Rainfall Shocks on the Evolution of Cognitive and Non-cognitive Skills. *Working Paper. Unversity of Pennsylvania.*

Liu, J., Raine, A., Venables, P. H., and Mednick, S. A. (2004). Malnutrition at age 3 years and externalizing behavior problems at ages 8, 11, and 17 years. American Journal of Psychiatry, 161(11), 2005-2013.

Lupien, S. J., McEwen, B. S., Gunnar, M. R., and Heim, C. 2009. Effects of stress throughout the lifespan on the brain, behaviour and cognition. *Nature Reviews Neuroscience*, 10(6): 434-445.

McCarthy, Dorothea. *Manual for the McCarthy scales of children's abilities.* Psychological Corporation, 1972.

Maccini, Sharon, and Dean Yang. 2009. Under the weather: health, schooling, and economic consequences of early-life rainfall. *American Economic Review* 99 (3): 1006-1026.

Macours, Karen, Norbert Schady, and Renos Vakis. "Cash transfers, behavioral changes, and cognitive development in early childhood: Evidence from a randomized experiment. *American Economic Journal: Applied Economics* 4.2 (2012): 247-273.

Majerus, Steve, and Martial Van der Linden. "Memory disorders in children." Pediatric Neurology Part 1. Handbook of clinical neurology 111 (2013): 251-255.

Markgraf, Vera, and Henry Diaz. 2000. *El Niño and the Southern Oscillation, Multiscale Variability and Global and Regional Impacts.* Cambridge, MA: Cambridge University Press.

McCarthy, Dorothea. *Manual for the McCarthy scales of children's abilities.* Psychological Corporation, 1972.

Mitchell, Timothy D. 2005. An improved method of constructing a database of monthly climate observations and associated high resolution grids. *International Journal of Climatology* 25: 693-712.

Morgane, Peter J., Robert Austin-LaFrance, Joseph Bronzino, John Tonkiss, Sofia Diaz-Cintra, L. Cintra, Tom Kemper, and Janina R. Galler. (1993) Prenatal malnutrition and development of the brain. Neuroscience and Biobehavioral Reviews 17(1): 91-128.

Munshi, Kaivan. 2003. Networks in the modern economy: Mexican migrants in the U.S. labor market. *Quarterly Journal of Economics* 118 (2): 549-599.

Neelin, J. David, David S. Battisti, Anthony C. Hirst, Fei-Fei Jin, Yoshinobu Wakata, Toshio Yamagata, and Stephen E. Zebiak. ENSO theory. *Journal of Geophysical Research: Oceans* 103:14261-14290.

Ozer, Emily J., Lia CH Fernald, James G. Manley, and Paul J. Gertler. "Effects of a Conditional Cash Transfer Program on Children?s Behavior Problems." Pediatrics 123, no. 4 (2009): e630-e637.

Paxson, Christina, and Norbert Schady. 2008. *Does money matter? The effects of cash transfers on child health and development in rural Ecuador.* Policy Research Working Paper no. 4226. World Bank, Washington DC.

Pechtel, P., and D.A. Pizzagalli. 2011. Effects of Early Life Stress on Cognitive and Affective Function: An Integrated Review of Human Literature. *Psychopharmacology* 214(1): 55D70.

Pereda, Paula C., Tatiane A. de Menezes, Denisard Alves. Climate change impacts on birth outcomes in Brazil *IDB Working Paper Series* 495.

Philander, S. George. 1990. *El Niño, La Niña and the Southern Oscillation.* San Diego, CA: Academic Press.

Polatajko, Helene J., and Noemi Cantin. 2005. “Developmental coordination disorder (dyspraxia): an overview of the state of the art." In Seminars in pediatric neurology, vol. 12, no. 4, pp. 250-258.

Revell, Clifford G., Stephen W. Goulter. 1986. South Pacific tropical cyclones and the Southern Oscillation. *Monthly Weather Review* 114: 1138-1145.

Ropelewski, C. F., and M. S. Halpert. 1987: Global and regional scale precipitation patterns associated with the El Niño Southern Oscillation. *Monthly Weather Review* 115: 1606-1626.

Rasmusson, Eugene M., and Thomas H. Carpenter. 1982. Variations in tropical sea surface temperature and surface wind fields associated with the Southern Oscillation El Niño. *Monthly Weather Review* 110: 354-384.

Rosales-Rueda, M.F., 2016. Impact of Early Life Shocks on Human Capital Formation: Evidence from El Nino Floods in Ecuador. University of California Irvine. Working paper.

Ruiz-Argüelles, Guillermo, and Antonio Llorente-Peters. 1981. Predicción Algebraica de Parámetros de Serie Roja de Adultos Sanos Residentes en Alturas de 0 a 2,670 Metros. *La Revista de Investigación Clínica* 33: 191-193.

Secretaria de Agricultura, Ganadería, Desarrollo Rural, Pesca y Alimentacion. 2007. *Situación actual y perspectivas del maíz en México, 1996-2012.*

Scholte, Robert S., Gerard J. van den Berg, and Maarten Lindeboom. 2015. Long-run effects of gestation during the Dutch Hunger Winter famine on labor market and hospitalization outcomes. *Journal of health economics* 39: 17-30.

Schrank, F.A., 2010. Chapter 31, Woodcock-Johnson III Tests of Cognitive Abilities. In Davis, Andrew S., and Rik Carl D'Amato, eds. *Handbook of pediatric neuropsychology.* Springer Publishing Company.

Schrank, F. A., Miller, D. C., Wendling, B. J., and Woodcock, R. W. (2010). Essentials of WJ III cognitive abilities assessment (Vol. 80). John Wiley and Sons.

Schrank, F. A., McGrew, K. S., and Dailey, D. E. H. (2010). Technical Supplement. Woodcock-Muñoz Language Survey Revised Normative Update. Rolling Meadows, IL: Riverside Publishing.

Shah, Manisha and Bryce Millett Steinberg 2017. Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital *Journal of Political Economy*125:2, 527-561.

SEDESOL. 1999. *Evaluación de Resultados del Programa de Educación, Salud y Alimentación. Primeros Avances.* Mexico City: SEDESOL.

SEDESOL. "Indicadores de Resultados." Accessed: November 13, 2011.

Skoufias, Emmanuel, Benjamin Davis, and Jere Behrman. 1999. Final report: an evaluation of the selection of beneficiary households in the Education, Health, and Nutrition Program (PROGRESA) of Mexico. Washington, DC.: International Food Policy Research Institute. IFPRI.

Skoufias, Emmanuel. 2001. PROGRESA and its impacts on the human capital and welfare of households in rural Mexico: a synthesis of the results of an evaluation by IFPRI. Washington, DC.: International Food Policy Research Institute. IFPRI.

Smith, Martin, A. Segeren, L. Santos Pereira, A. Perrier, and R. Allen. 1991. "Report on the Expert Consultation on Procedures for Revision of FAO Guidelines for Prediction of Crop Water Requirements. Held in FAO, Rome, Italy, 28-31 May 1990."

Sponberg, K. 1999. *Navigating the numbers of climatological impact. Compendium of Climatological Impacts, University Corporation for Atmospheric Research*, Vol. 1. National Oceanic and Atmospheric Administration, Office of Global Programs, 13 pp.

Stevenson, H. W., and Newman, R. S. 1986. Long-term prediction of achievement and attitudes in mathematics and reading. *Child development*, 57: 646-659.

UCAR. 1994. *El Niño and climate prediction. Reports to the Nation on our Changing Planet.* UCAR, No. 3, 25.

UNICEF. 2007. *Progress for Children. A World Fit for Children: Statistical Review.* New York: UNICEF.

Van Garderen, D. (2006). Spatial visualization, visual imagery, and mathematical problem solving of students with varying abilities. Journal of Learning Disabilities, 39(6), 496-506.

Vecchi, Gabriel A., and Andrew Wittemberg. 2010. El Niño and our future climate: where do we stand? *Wiley Interdisciplinary Reviews: Climate Change* 1: 260-270.

Vicarelli, Marta. 2011. Exogenous Income Shocks and Consumption Smoothing: Strategies among Rural Households in Mexico. PhD. Dissertation. Columbia University, New York, NY.

Walker, Susan P., Susan M. Chang, Christine A. Powell, Emily Simonoff, and Sally M. Grantham-McGregor. (2006) "Effects of psychosocial stimulation and dietary supplementation in early childhood on psychosocial functioning in late adolescence: follow-up of randomised controlled trial." British Medical Journal (BMJ) 333, no. 7566: 472-474.

Walker, S. P., Wachs, T. D., Gardner, J. M., Lozoff, B., Wasserman, G. A., Pollitt, E., and International Child Development Steering Group. (2007). Child development: risk factors for adverse outcomes in developing countries. The lancet, 369(9556), 145-157.

Walker SP, S.M. Chang, C.M. Vera-Hernandez, S. Grantham-McGregor 2011. Early childhood stimulation benefits adult competence and reduces violent behaviour. Pediatrics;127:849-57

Wilson, Peter H., and Beryl E. McKenzie. 1998. "Information processing deficits associated with developmental coordination disorder: A meta-analysis of research findings." The Journal of Child Psychology and Psychiatry and allied disciplines 39, no. 6: 829-840.

Woodward, L. J., Edgin, J. O., Thompson, D., and Inder, T. E. (2005). Object working memory deficits predicted by early brain injury and development in the preterm infant. Brain, 128(11), 2578-2587.

World Health Organization. 1996. *Catalogue of Health Indicators*. Geneva: World Health Organization.

World Health Organization. 2008. *Worldwide Prevalence of Anaemia 1993-2005*. Geneva: World Health Organization.

Wu, Peili, Nikolaos Christidis, and Peter Stott (2013) Anthropogenic impact on Earth's hydrological cycle. *Nature Climate Change* 3, 807-810.

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 (Peabody, std)	3339	0.0138	0.9855	-1.1708	5.4739
LT memory (WM 1, std)	4111	0.0495	1.0123	-1.1284	4.5431
ST memory (WM 2, std)	4111	0.1387	0.9337	-1.9120	3.0769
visual-spatial (WM 3, std)	4111	0.0688	0.9717	-1.4832	4.8456
Motor skills					
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 Poverty index (1997)	2565	713.7564	134.8384	286	1238.75
HH size (1997)	2569	5.6781	2.4907	1	24
HH head language					
* spanish & indigenous	4111	0.3490	0.4767	0	1
* only indigenous	4111	0.0248	0.1555	0	1
Rainfall Measures					
Std. Precip. Sep., 1998	4111	0.9458	0.7595	-0.4561	2.4682
Std. Precip. Oct., 1998	4111	0.6191	0.5182	-0.4676	1.7105
Std. Precip. Sep., 1999	4111	-0.4809	0.1481	-0.7370	-0.1493
Std. Precip. Oct., 1999	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

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 $rain\_shock_j = 0$ (1)	Mean $rain\_shock_j = 1$ (2)	Difference (3)	t-statistic (4)
Village characteristics				
male avg. wages	315.7	300.6	15.11	1.183
female avg. wages	42.31	43.61	-1.299	-0.350
Household characteristics and assets				
size	5.507	5.750	-0.243	-1.587
Poverty index	720.3	721.6	-1.243	-0.101
owns land (ha)	1.485	1.527	-0.0420	-0.231
own house (binary)	0.923	0.903	0.0202	0.977
electricity (binary)	0.755	0.758	-0.00241	-0.0557
water (binary)	0.0463	0.0398	0.00657	0.492
tv (binary)	0.585	0.461	0.125**	3.151
vehicle (binary)	0.123	0.0704	0.0525*	2.274
donkeys	0.372	0.369	0.00249	0.0359
bullocks	0.219	0.209	0.00975	0.0588
sheep	1.397	1.218	0.179	0.404
chickens	6.469	7.116	-0.647	-1.080
pigs	1.137	1.265	-0.128	-0.709
Household migratory characteristics				
temporary migrants	0.227	0.156	0.0718*	2.535
permanent migrants	0.0189	0.0163	0.00256	0.271
Head of household characteristics				
male (binary)	0.888	0.872	0.0156	0.719
age (years)	38.35	38.02	0.332	0.312
education (years)	3.836	3.553	0.283	1.280
agric worker	0.672	0.718	-0.0458	-1.279
language spoken:				
Indigenous	0.274	0.594	-0.320***	-5.283
Spanish & Indigen.	0.00885	0.203	-0.194***	-4.996

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of the 1999 September-October rainfall shock on cognitive development indicators measured in 2003 for children born between 1997 and 2001. (Outcomes are standardized test scores).

	Peabody Test[a]	**Woodcock-Muñoz Test**[b]		
		WM1	WM2	WM3
		working/long	short term	visual spatial
	language	term memory	memory	thinking
	(1)	(2)	(3)	(4)
Panel A				
coh97-00 × rain_shock[c]	-0.136	-0.153	-0.0543	-0.161
	[0.0680]*	[0.0559]***	[0.0471]	[0.0602]***
	(.0627)⋆⋆	(0.0598)⋆⋆⋆	(0.0513)	(0.0673)⋆⋆
coh01 × rain_shock		0.0211	-0.0673	-0.0109
		[0.0408]	[0.0752]	[0.0676]
		(0.0438)	(0.0730)	(0.0591)
Panel B				
coh97 × rain_shock	-0.598	-0.305	-0.0387	-0.289
	[0.1603]***	[0.1216]**	[0.0759]	[0.1168]**
	(0.1459)⋆⋆⋆	(0.1461)⋆⋆	(0.0776)	(0.1319)⋆⋆
coh98 × rain_shock	-0.193	-0.207	-0.0576	-0.205
	[0.0992]*	[0.0719]***	[0.0570]	[0.0814]**
	(0.1016)⋆	(0.0797)⋆⋆⋆	(0.0663)	(.0918)⋆⋆
coh99 × rain_shock	-0.00498	-0.108	-0.0766	-0.110
	[0.0696]	[0.0718]	[0.0609]	[0.0693]
	(0.0666)	(0.0741)	(0.0560)	(.0702)
coh00 × rain_shock	0.0149	-0.0712	-0.0276	-0.113
	[0.0563]	[0.0544]	[0.0502]	[0.0547]**
	(0.0521)	(0.0466)	(0.0501)	(0.0542)⋆⋆
coh01 × rain_shock		0.0211	-0.0670	-0.0138
		[0.0406]	[0.0758]	[0.0690]
		(0.0435)	(0.0735)	(0.0603)
Observations	3339	4111	4111	4111
R^2	0.35	0.26	0.50	0.42
Mean	0.0138	0.0495	0.139	0.0688

Controlling for *age* (months), *age*^{2}, *gender*, *father's language*, *HH structure*, *cohorts*.

Standard errors clustered by grid in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Conley standard errors in parentheses (cutoff= 1 degree). ⋆ $p < 0.10$, ⋆⋆ $p < 0.05$, ⋆⋆⋆ $p < 0.01$

[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 interaction between the variable *coh97-00* (=1 if the child was born between 1997 and 2000) and the variable *rain_ shock* (=1 if a rainfall shock occurred in 1999. The rainfall shock is defined as the rainfall in a given grid in September or October being 0.7 standard deviations above its long-term (1961-1999) average).

Table 4: Effect of the 1999 September-October rainfall shock on anthropometric indicators, measured in 2003, for children born between 1997 and 2001.

	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]	-0.112	-0.142	0.157	0.0770	-0.0524
	[0.0604]*	[0.0550]**	[0.0599]**	[0.1120]	[0.0950]
	(0.0646)⋆	(.0626)⋆⋆	(0.0641)⋆⋆	(0.1178)	(0.1068)
coh01 × rain_shock	-0.0558	-0.0898	0.0742	0.114	-0.0434
	[0.0603]	[0.0595]	[0.0924]	[0.3453]	[0.0825]
	(0.0703)	(0.0650)	(0.0919)	(0.2731)	(0.0824)
Panel B					
coh97 × rain_shock	-0.252	-0.198		0.424	-0.0609
	[0.1218]**	[0.0680]***		[0.2481]*	[0.1022]
	(0.1081)⋆⋆	(0.0665)⋆⋆		(0.2022)⋆⋆	(0.1037)
coh98 × rain_shock	-0.151	-0.184	0.153	0.148	-0.0888
	[0.0860]*	[0.0618]***	[0.0757]**	[0.1419]	[0.0955]
	(0.0870)⋆	(0.0682)⋆⋆⋆	(.0732)⋆⋆	(0.1365)	(0.1069)
coh99 × rain_shock	-0.113	-0.102	0.149	-0.108	-0.0372
	[0.0687]	[0.0658]	[0.0630]**	[0.1852]	[0.1026]
	(0.0711)	(0.0737)	(.0708)⋆⋆	(0.1751)	(0.1165)
coh00 × rain_shock	-0.000894	-0.110	0.168	0.0598	-0.0247
	[0.0450]	[0.0595]*	[0.0636]**	[0.2286]	[0.0910]
	(0.0538)	(0.0668)⋆	(.0648)⋆⋆	(0.2433)	(0.1005)
coh01 × rain_shock	-0.0553	-0.0898	0.0742	0.118	-0.0418
	[0.0610]	[0.0596]	[0.0925]	[0.3456]	[0.0823]
	(0.0707)	(0.0649)	(.0921)	(0.2726)	(0.0824)
Observations	4111	4111	2912	4111	4111
R^2	0.47	0.70	0.06	0.01	0.06
Mean	0.109	0.132	0.345	1.326	0.750

Controlling for *age* (months), *age*^{2}, *gender*, *father's language*, *HH structure*, *cohorts*.

Standard errors clustered by grid in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Conley standard errors in parentheses (cutoff= 1 degree). ⋆ $p < 0.10$, ⋆⋆ $p < 0.05$, ⋆⋆⋆ $p < 0.01$

[a] *weight* and *height* are 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 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 interaction between the variable *coh97-00* (=1 if the child was born between 1997 and 2000) and the variable *rain_shock* (=1 if a rainfall shock occurred in 1999. The rainfall shock is defined as the rainfall in a given grid in September or October being 0.7 standard deviations above its long-term (1961-1999) average).

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 2001. (Outcomes for McCarthy test scores, depression and aggression indexes are standardized).

	McCarthy[a]	**Achenbach Child Behavioral Checklist**[b]	
		Anxiety & Depression	Aggressive Behaviour
	(1)	(2)	(3)
Panel A			
coh97-00 × rain_shock[c]	0.00981	0.190	-0.0283
	[0.0431]	[0.0407]***	[0.0496]
	(0.0465)	(0.0403)⋆⋆⋆	(0.0533)
coh01 × rain_shock	-0.0609	0.189	0.118
	[0.1141]	[0.0845]**	[0.1196]
	(0.0918)	(0.0784)⋆⋆	(0.1117)
Panel B			
coh97 × rain_shock	0.102	0.198	-0.126
	[0.0459]**	[0.1216]	[0.1351]
	(0.0528)⋆	(0.1081)⋆	(0.1135)
coh98 × rain_shock	0.0425	0.157	-0.0109
	[0.0396]	[0.0644]**	[0.0690]
	(0.0401)	(0.0571)⋆⋆⋆	(0.0652)
coh99 × rain_shock	-0.00987	0.160	0.0464
	[0.0551]	[0.0520]***	[0.0635]
	(0.0606)	(0.0479)⋆⋆⋆	(0.0690)
coh00 × rain_shock	-0.0476	0.271	-0.109
	[0.0833]	[0.0682]***	[0.0828]
	(0.0799)	(0.0715) ⋆⋆⋆	(0.0827)
coh01 × rain_shock	-0.0614	0.189	0.119
	[0.1145]	[0.0858]**	[0.1196]
	(0.0918)	(0.0790)⋆⋆	(0.1115)
Observations	4111	4111	4111
R^2	0.42	0.02	0.01
Mean	0.0757	-0.0149	0.0376

Controlling for *age* (months), *age*^{2}, *gender*, *father's language*, *HH structure*, *cohorts*.

Standard errors clustered by grid in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Conley standard errors in parentheses (cutoff= 1 degree). ⋆ $p < 0.10$, ⋆⋆ $p < 0.05$, ⋆⋆⋆ $p < 0.01$

[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. Results for each exercise are combined into a single indicator.

[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 interaction between the variable *coh97-00* (=1 if the child was born between 1997 and 2000) and the variable *rain_shock* (=1 if a rainfall shock occurred in 1999. The rainfall shock is defined as the rainfall in a given grid in Sept or Oct being 0.7 SDs above its long-term average).

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. Formal transfers include food and other forms of government aid. Informal transfers include food and other transfers from either a family member or from a neighbor.

Dependent Variables	Binary Variable (✓)[a]	Coefficient[b]	Std_Dev
Total household income (log)			
$income_t$		-0.1874***	(0.065)
$income_{t+1}$		-0.3439***	(0.081)
Household income from agriculture (log)			
$agricultural\_income_t$		-0.3275***	(0.062)
$agricultural\_income_{t+1}$		-0.2424***	(0.057)
=1 if household received government aid			
$food\_aid_t$	✓	0.0725***	(0.019)
$other\_aid_t$	✓	0.0753*	(0.043)
=1 if household received informal transfers			
$from\_family_t$	✓	-0.0143***	(0.005)
$from\_neighbor_t$	✓	-0.0150**	(0.007)

Standard errors clustered by grid in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] Indicates if the dependent variable is a dummy.

[b] Each line shows the result of a different regression where equation (3) 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 *HH structure*.

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)		
$food\_consumption_t$ [pesos]	-0.0663	(0.043)
$food\_consumption_{t+1}$ [pesos]	-0.1515**	(0.068)
$food\_consumption_t$ [kg]	0.0407	(0.040)
$food\_consumption_{t+1}$ [kg]	0.0148	(0.081)
$food\_consumption_t$ [calories]	0.058	(0.038)
$food\_consumption_{t+1}$ [calories]	0.013	(0.086)
Diet composition (log)		
$tortilla\_consumption_t$ [pesos]	0.0933	(0.091)
$tortilla\_consumption_{t+1}$ [pesos]	-0.1432	(0.086)
$animal\_consumption_t$ [pesos]	-0.2014**	(0.099)
$animal\_consumption_{t+1}$ [pesos]	-0.3005***	(0.099)
$fruit\_and\_vegetable\_consumption_t$ [pesos]	-0.0400	(0.070)
$fruit\_and\_vegetable\_consumption_{t+1}$ [pesos]	-0.1519**	(0.071)
Children reported sick by the mother		
$children\_sick_t$ (% in the HH)	0.0090	(0.032)
$children\_sick_{t+1}$ (% in the HH)	-0.0313	(0.031)
Medicine Expenditure (log)		
$medicine\_expenditures_t$	-0.4253***	(0.148)
$medicine\_expenditures_{t+1}$	0.2262	(0.208)

Standard errors clustered by grid in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] Each line shows the result of a different regression where equation (3) 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 *HH structure*.

Table 8: The mitigating effect of Progresa in villages exposed to the rainfall shock. These results are associated to the anthropometric, health, and cognitive development indicators collected in 2003. Coefficients are estimated using the randomized experiment empirical specification (equation 4).

Panel A. Cognitive Development Indicators

	Peabody Test	**Woodcock-Muñoz Test**		
	language (1)	long term memory (2)	short term memory (3)	visual-spatial thinking (4)
Treatment x Coh97-00	-0.0148	0.0114	-0.0213	-0.0754
	[0.0706]	[0.0731]	[0.0418]	[0.0706]
Rain shock x Coh97-00	-0.0883	-0.0840	-0.0796	-0.154*
	[0.0848]	[0.0797]	[0.0537]	[0.0868]
Treatment x Rain x Coh97-00	-0.0795	-0.116	0.0436	-0.00818
	[0.0901]	[0.0942]	[0.0649]	[0.0899]
Observations	3339	4111	4111	4111

Panel B. Anthropometric and Health Indicators

	weight (std) (1)	height (std) (2)	Stunting (3)	Anemia (4)	Days_sick (5)
Treatment[a] x Coh97-00[b]	-0.0927	-0.0406	0.0419	0.139**	-0.00238
	[0.0614]	[0.0482]	[0.0341]	[0.0669]	[0.2150]
Rain shock[c] x Coh97-00	-0.117	-0.111*	0.130**	-0.0220	0.0738
	[0.0722]	[0.0562]	[0.0512]	[0.1154]	[0.1995]
Treatment x Rain x Coh97-00	0.0139	-0.0499	0.0436	-0.0584	0.00425
	[0.0820]	[0.0712]	[0.0618]	[0.0904]	[0.2697]
Observations	4111	4111	2912	4111	4111

Panel C. Motor Development Indicators

	McCarthy (1)	Depress (2)	Agress (3)
Treatment x Coh97-00	0.0852	0.0486	-0.000793
	[0.0556]	[0.0529]	[0.0581]
Rain shock x Coh97-00	0.113**	0.221***	-0.0370
	[0.0543]	[0.0529]	[0.0631]
Treatment x Rain x Coh97-00	-0.178**	-0.0538	0.0146
	[0.0707]	[0.0674]	[0.0866]
Observations	4111	4111	4111

Standard errors clustered by grid in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] $Treatment = 1$ if village was randomly selected to receive PROGRESA.
[b] $coh97 - 00 = 1$ if the child was born between 1997 and 2000.
[c] $rain\_shock = 1$ if a rainfall shock occurred in 1999.

Table 9: The mitigating effect of Progresa in villages exposed to the rainfall shock. These results are associated to the anthropometric, health, and cognitive development indicators collected in 2003. Coefficients are estimated using the randomized experiment empirical specification (equation 5).

Cognitive Development Indicators

	Peabody Test	**Woodcock-Muñoz Test**		
	language	long term memory	short term memory	visual-spatial thinking
	(1)	(2)	(3)	(4)
$\mathbb{1}(x\_pmt > 0)$	-0.0347	0.311	-0.0930	0.0686
	[0.3960]	[0.3803]	[0.3447]	[0.3660]
$rain\_shock$	-0.284	-0.415**	-0.273	-0.579***
	[0.1926]	[0.1896]	[0.1718]	[0.1824]
$rain\_shock \times \mathbb{1}(x\_pmt > 0)$	-0.0670	0.0231	0.176	0.102
	[0.4796]	[0.4606]	[0.4174]	[0.4432]
Observations	1103	1209	1209	1209

Anthropometric and Health Indicators

	weight (std)	height (std)	Stunting	Anemia	Days_sick
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}(x\_pmt > 0)$[a]	0.0714	-0.0147	-0.118	0.0238	1.340
	[0.3410]	[0.3427]	[0.2422]	[0.1653]	[0.9826]
$rain\_shock$[b]	-0.382**	-0.408**	0.391***	-0.0196	0.800
	[0.1700]	[0.1708]	[0.1170]	[0.0824]	[0.4898]
$rain\_shock \times \mathbb{1}(x\_pmt > 0)$	0.179	0.170	0.0817	-0.172	-2.702**
	[0.4130]	[0.4150]	[0.2863]	[0.2002]	[1.1899]
Observations	1209	1209	786	1209	1209

Motor Development Indicators

	McCarthy	Depress	Agress
	(1)	(2)	(3)
$\mathbb{1}(x\_pmt > 0)$	-0.144	-0.366	0.0732
	[0.3252]	[0.3842]	[0.3950]
$rain\_shock$	-0.303*	0.283	-0.0253
	[0.1621]	[0.1915]	[0.1969]
$rain\_shock \times \mathbb{1}(x\_pmt > 0)$	0.161	0.494	-0.180
	[0.3938]	[0.4652]	[0.4783]
Observations	1209	1209	1209

Robust standard errors [in brackets]. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] $rain\_shock = 1$ if village had a flood occurrence in 1999.

[b] $\mathbb{1}(x\_pmt > 0)$ indicates if household is eligible to receive PROGRESA.

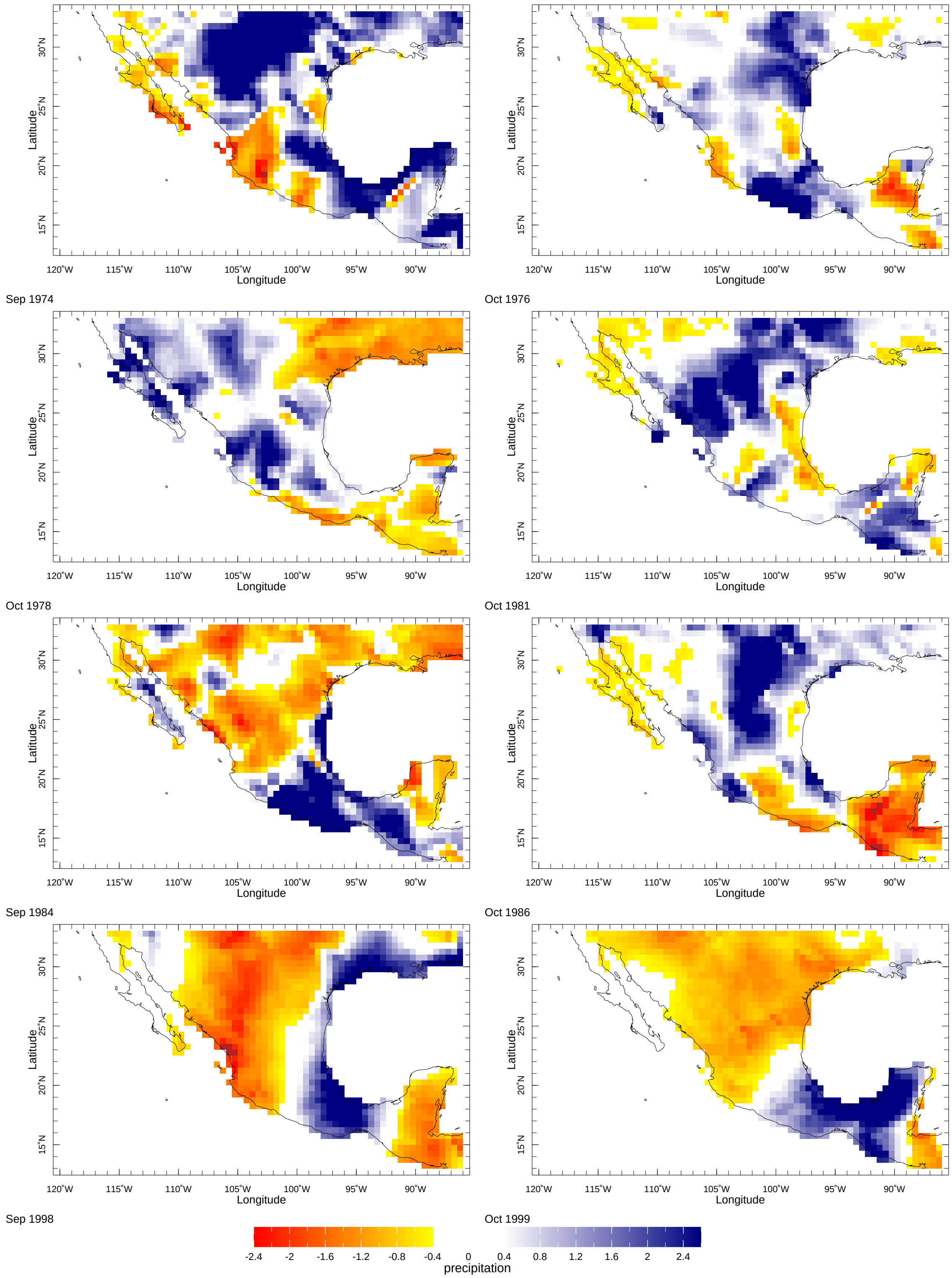

Figure 1: Spatial distribution of extreme precipitation events associated to La Niña episodes, in Mexico, during harvest season, in different years. Extreme precipitation patterns during La Niña events are not consistent; indeed, historically, since 1974, they have varied substantially between different La Niña events. The figure includes the following years: 1974 1976, 1978, 1981, 1984, 1986, 1998 and 1999. The La Niña episodes in **1998** and **1999** are the ones analyzed in this paper.

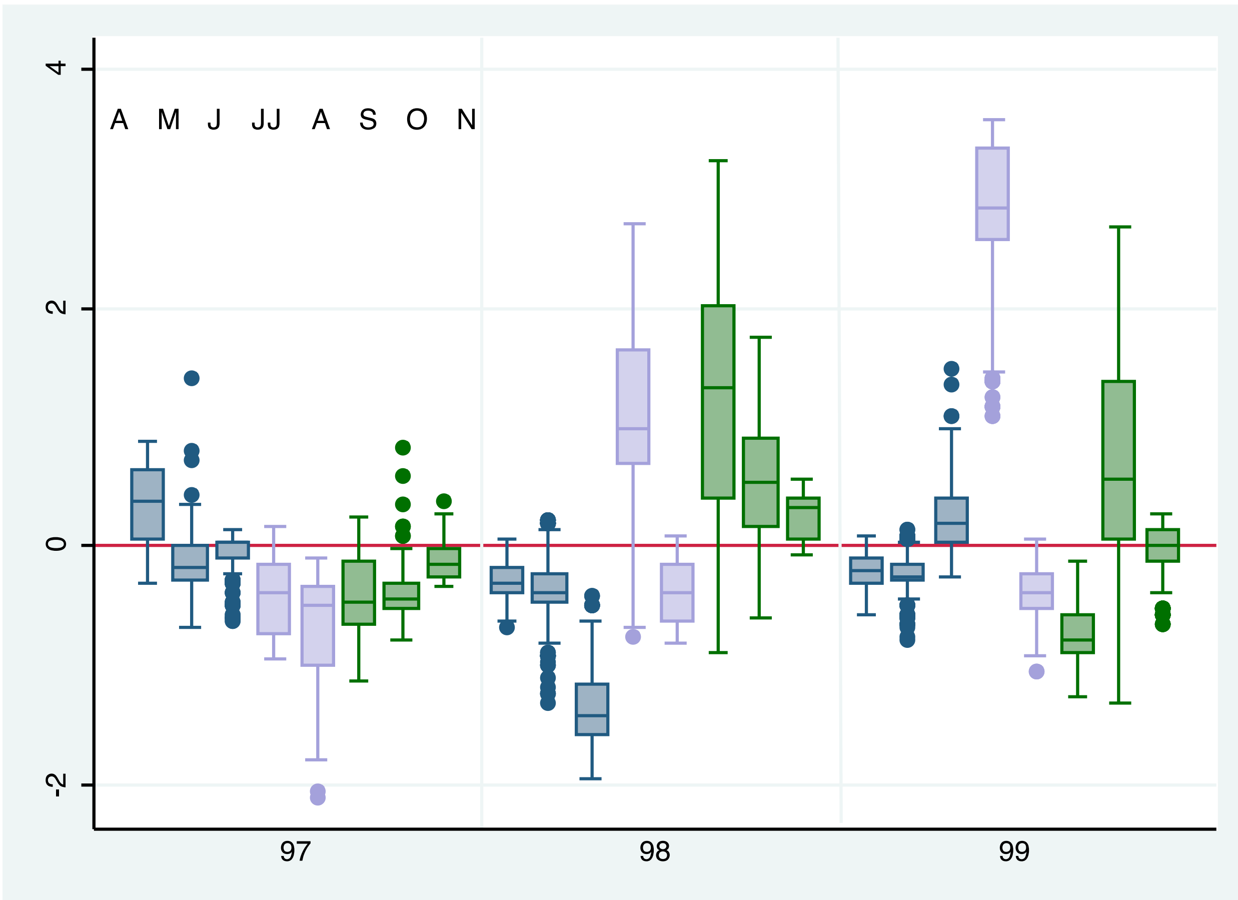

Figure 2: Distribution of Monthly Precipitation Standardized Anomalies.

This figure reproduces figure 1 in Vicarelli (2011). The x-axis represents the 1997, 1998 and 1999 agricultural seasons for maize. The agricultural season lasts eight months, from April to November, and includes the following phases : planting Phase (April-June); growing phase (July to August); and maturation and harvesting (September to November). The y-axis represent that average monthly precipitation standardized anomaly for the grid-cells where the Progresa villages are located. The unit of observation is a 0.5 x 0.5 degree grid-cell (Total=55 grid-cells). For each grid-cell, the monthly standardized deviation from the 1961-1999 mean is calculated.

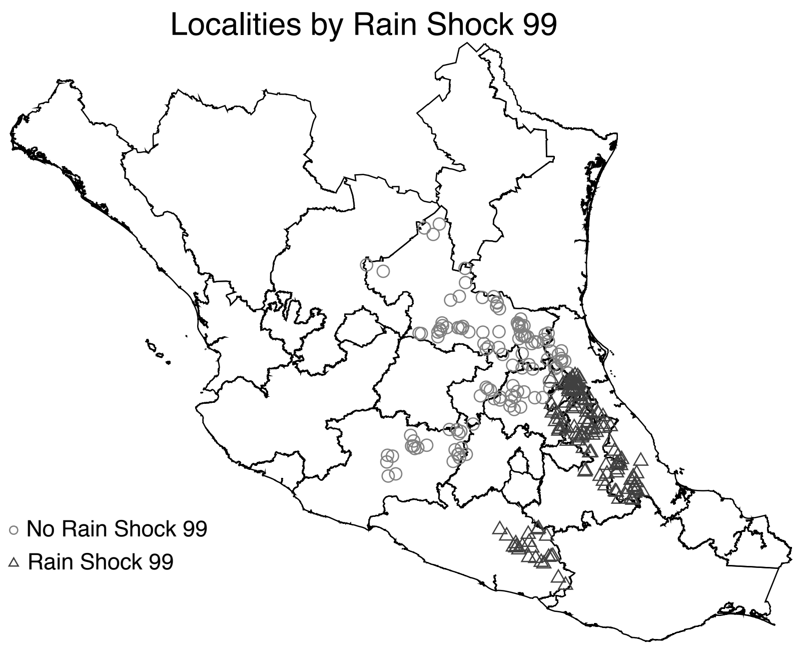

Figure 3: Localities affected by Rain Shock 1999

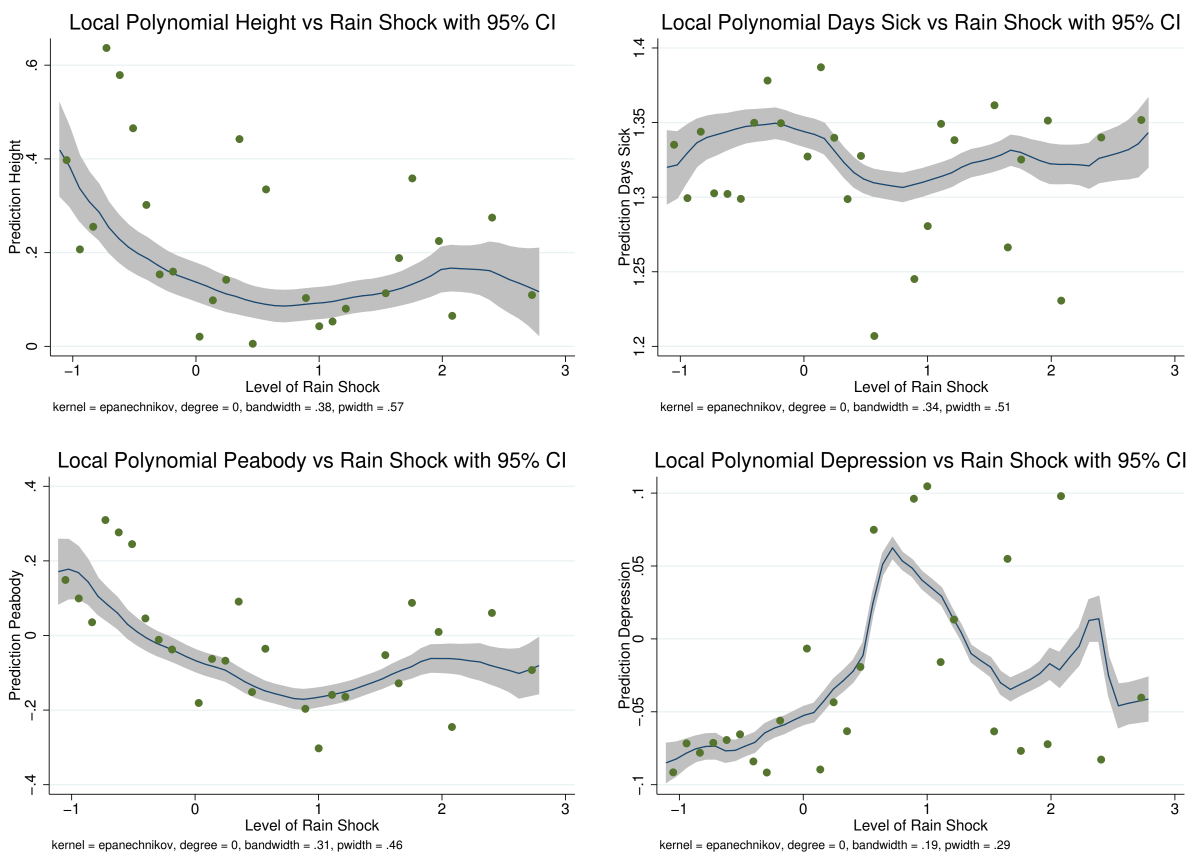

Figure 4: Main outcomes' levels by amount of rainfall in 1999 harvest season

On each graph, the y-axis corresponds to the residuals of a regression of the outcome of interest against cohorts and controls. The x-axis corresponds to the standardized precipitation anomaly level in October 1999. Each dot represents a conditional mean for a 0.1 interval, the line is a local polynomial regression and the shaded area is its corresponding 95% confidence interval.

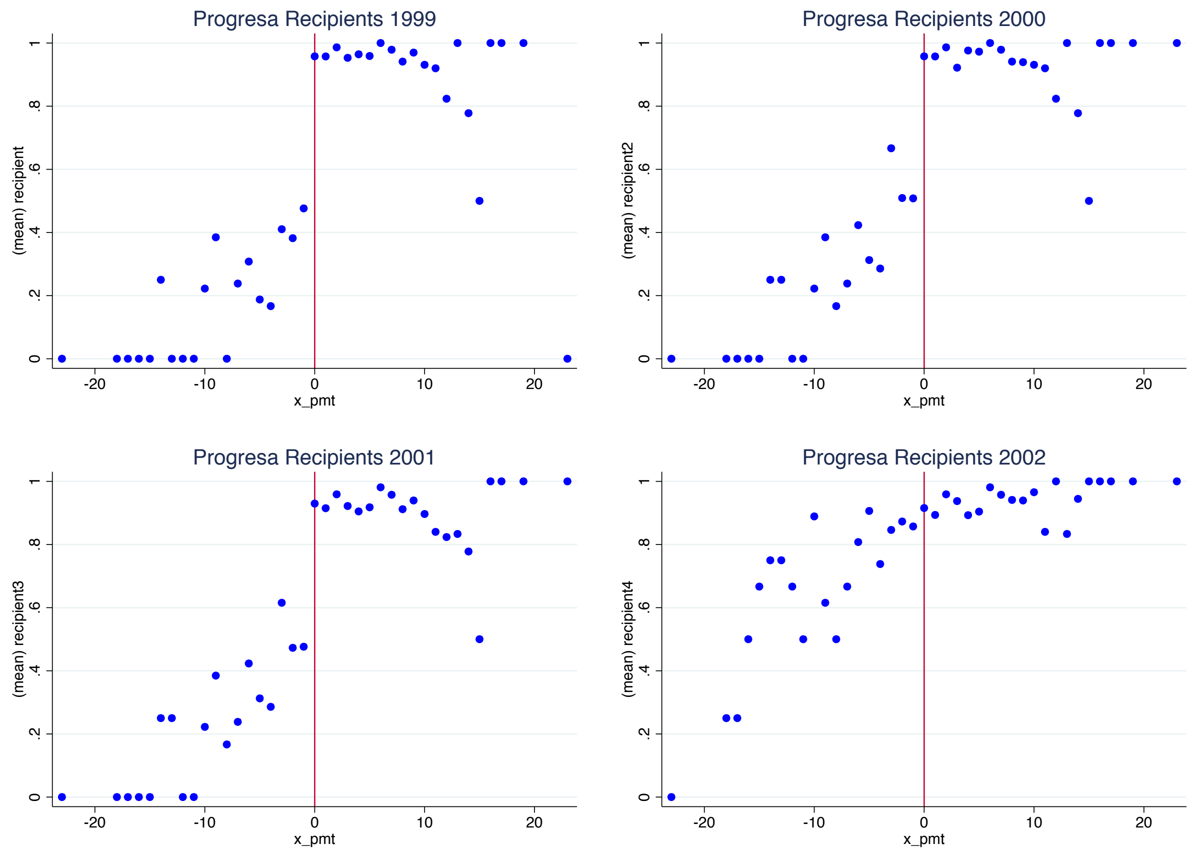

Figure 5: Regression Discontinuity: First Stage

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 (x_pmt) is formed with a formula that weights household's asset ownership and socio-economic characteristics of its members.
Analysis restricted to original randomized treatment villages.
The y-axis gives the proportion of households that report receiving the cash transfers of the program. Perfect targeting and take-up rates would yield a sharp regression discontinuity on the 1999-2001 graphs