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

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Abstract

El Niño Southern Oscillation (ENSO) is a recurrent climatic event that causes severe weather shocks. This paper employs ENSO-related floods at the end of the agricultural season to identify medium-term effects of negative conditions in early child development. The analysis shows that, four to five years after the shock, children exposed to it during their early stages of life have test scores in language development, working-memory, and visual-spatial thinking abilities that are 11 to 21 percent lower than same aged children not exposed to the shock. Negative effects are also found on anthropometric characteristics: children affected during their early life stages exhibit lower height (0.42 to 0.71 inches), higher likelihood of stunting (11 to 14 percentage points), and lower weight (0.84 pounds) than same aged children not affected by the shock. Negative effects of weather shocks on income, food consumption, and diet composition during early childhood appear to be key mechanisms behind the impacts on children's outcomes. Finally, no mitigation effects were found from the provision of the Mexican conditional cash transfer program *Progresa* on poor rural households with children affected by ENSO-related shocks.

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1 Introduction

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, Townsend and Vickery 2008). Young children and pregnant women represent particularly sensitive populations to events of this nature. The idea that stimuli or stressful conditions during critical periods in early life can have lifetime consequences is well established in developmental biology (Barker 1998). Previous work in the economics literature has also shown how pervasive conditions (e.g. malnutrition, sickness, pollution, etc.) in-utero and during the first years of life have considerable long-term consequences. Some of these studies identify effects of early life conditions on outcomes at adulthood, such as income, health, educational attainment, and physical and mental disabilities (Alderman et. al. 2003; Almond 2006; Almond and Mazumder 2011; Maccini and Yang 2009).

This paper investigates medium-term consequences of negative conditions experienced during early stages of life on children's physical and cognitive development. Test scores for language development, working and long-term memory, and visual-spatial thinking provide information about specific dimensions of cognitive development. This information, added to objective anthropometric measures (like height and weight) and gross motor skills, has been proven as a strong predictor of success later in adulthood (Case and Paxson 2006; Grantham-McGregor et al. 2007). Therefore, identifying medium-term impacts of early-life conditions on these indicators provides valuable information about the channels that might be driving previously identified long-term impacts.

Weather events have been widely used in the economics literature as instruments. Some examples include hurricanes, droughts, and rainfall events. To identify negative early-life conditions, this paper employs extreme precipitation shocks[1] that occurred during the 1998-1999 maize harvest seasons and were related to the "El Niño Southern Oscillation" (ENSO) climatic event. The occurrence of these shocks severely compromised crop outputs (SAGARPA 2008). Using geographical variation in precipitation, we compare health,

[1] The terms "extreme precipitation shocks" and "floods" are used interchangeably throughout the paper. Further details of the shocks identification are provided in *Section 3*.

anthropometric and cognitive development outcomes of children exposed at early stages of life to the shock versus same-aged children not exposed. The population of children under analysis spans different stages of early child development: from *in-utero* conditions up to their second year of life. The main identification assumption is that the occurrence of these shocks is exogenous and creates negative conditions that potentially affect children at early stages of life (in-utero and first years after birth).[2]

The study of these shocks is interesting given ENSO's characteristics. ENSO is a recurrent climatic event with a 5 to 7 year cycle. It develops in the Pacific Ocean and affects global 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 et al. 1999).[3] Climatologists indicate that ENSO cycles will continue to affect global climate, and events might become more frequent and intense with global warming (Vecchi and Wittemberg 2009). ENSO-related studies are therefore relevant from an economic, climatic, and public policy perspective. To the authors' knowledge this is the first study to investigate the impact of ENSO-related weather shocks on human capital formation.

The data used in this study comes from a rich longitudinal household dataset gathered as part of Mexico's *Progresa* randomized poverty alleviation program.[4] The *Progresa* database is exceptional for size and data quality and includes biannual surveys from 1997 to 2000, as well as a detailed follow-up survey in 2003. This latter survey provides valuable information for children aged 2 to 6, namely, specific indicators of cognitive development, motor skills, as well as objective anthropometric and health indicators. Tests of high internal reliability and validity according to U.S. standards were used to provide cognitive development indicators: (i) the *Peabody Picture Vocabulary Test* was used to assess lan-

[2]Some negative consequences of the shocks include: compromising the household's (expected) income flow, thus affecting food consumption and nutrition, and creating an unhealthy and stressful environment, among others.

[3]Further details about ENSO can be found in *Section 2*.

[4]*Progresa* changed its name to *Oportunidades* in 2002 and up to date is Mexico's most comprehensive social program in operation.

guage development; and (ii) three sub-tests of the *Woodcock-Muñoz Test*[5] provided working and long-term memory, and visual-spatial thinking indicators (Schrank et al. 2005). Anthropometric and health variables include height, weight, hemoglobin, and self-reported health. Gross motor skill measures were obtained by administering the *McCarthy Scale of Children's Abilities Test*, and include balance and physical coordination.

To identify children exposed to ENSO-related weather shocks during their early stages of life, the *Progresa* database was spatially merged with a monthly precipitation gridded dataset using the child's household geographical location. 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). The magnitude of the deviation from the historical average monthly rainfall level in a given grid is used to identify extreme precipitation events.[6]

The main findings in this paper indicate medium-term negative effects of excessive rain shocks on cognitive and anthropometric indicators. Children exposed to the shock during the first two years of their life suffered the most severe consequences. Language development, working memory, and visual-spatial thinking test scores of these children are 21, 19, and 13 percent lower than same-aged children not exposed, respectively. Also, they exhibit lower weight (0.84 lb.), height (0.71 in.), and higher likelihood of stunting (13 percentage points). Similarly, children born the same year and up to one year after the shock obtain lower cognitive results (that range from 11 to 16 percent), lower height (0.49 in.), and higher likelihood of stunting (14 percentage points). No strong evidence of negative effects is found for gross motor skills.

Furthermore, the longitudinal structure of the dataset allows investigating which household's characteristics were most affected by the shock after its occurrence, and thus contributed to the negative medium-term consequences found in children. Our estimates show that the extreme rainfall events at the end of the harvest season represented an important negative income shock. Total household income, reported two months after the shock oc-

[5] Spanish version of the Woodcock-Johnson Tests of Cognitive Abilities.

[6] This is a standard practice recommended by climatologists (Heim 2002; Keyantash and Dracup 2004).

curred, was 39 percent lower for households living in regions exposed. This negative income effect persisted up to two years after the shock occurrence. The value of food consumption (per adult equivalents) was 10 to 15 percent lower when comparing households in exposed versus non-exposed regions. Diet composition also had significant effects: up to two years after the shock, households in affected regions significantly reduced their animal-origin protein consumption, as well as fruits and vegetables. Finally, mother's self-reported measures about their children's sickness did not show any short nor medium-term effect from the shocks.

The final part of this paper tests whether *Progresa*, a conditional cash transfer program targeting poor rural households, helped mitigating the negative effects of ENSO-related rainfall shocks. *Progresa's* randomized evaluation phase took place between 1997 and 2000, which coincides with the ENSO event analyzed in this paper. This regional and temporal coincidence provides a great opportunity to assess the possible benefits of *Progresa* as an insurance mechanism against rainfall shocks.

Two empirical strategies were used for the *Progresa* analysis. First, the randomization at the village level is employed.[7] Given that the outcomes analyzed come from the 2003 follow-up survey, the comparison should be interpreted as an early versus late random allocation (rather than treatment versus control). Second, a regression discontinuity design is estimated using the administrative rule to select beneficiaries. This analysis is able to identify effects of being a program beneficiary from its start (1998) with respect to early 2002.

No evidence of direct nor mitigating effects of *Progresa* on anthropometric and cognitive outcomes is found. Despite providing cash transfers that household's could choose how to spend, *Progresa* does not offset the negative effects on consumption and diet composition in the periods that follow the negative shock. Similarly, Paxson and Schady (2008) and Fernald and Gertler (2004) find slightly positive to no direct effects on anthropometric and

[7] Villages that were selected for treatment began receiving the benefits in May 1998 while control villages were added between February and May 2000.

cognitive development indicators from randomized poverty alleviation programs in Ecuador (*Bono de Desarrollo Humano*) and Mexico (*Progresa*), respectively.

The remainder of the paper is organized as follows. *Section 2* gives some background on ENSO and maize agriculture. *Section 3* describes the socioeconomic, child development and climatic datasets used. *Section 4* explains the identification strategy followed. *Section 5* details the results of the anthropometric, cognitive, and motor skills outcomes. *Section 6* analyzes the possible mechanisms that might be driving these medium-term outcomes. *Section 7* provides evidence from the *Progresa* analysis. Finally, *section 8* concludes.

2 Background on ENSO and its effects

2.1 El Niño Southern Oscillation (ENSO)

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*[8] (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 down towards a neutral state.

ENSO affects hydro-meteorological patterns around the world, causing extreme weather events such as droughts, floods, and heat waves (Ropelewski and Halpert 1987; Philander 1990; Neelin et al. 1998; Larkin et al. 2005). Its strongest impacts are observed in countries bordering the Pacific Ocean, from Latin America to Southeast-Asia; however, ENSO's consequences reach regions as far as India and Africa (Cane et al. 1994).

[8]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.

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. *El Niño* and *La Niña* events tend to differ for onset, magnitude, spatial extent, duration and cessation (Ropelewski and Halpert 1987; Philander 1990; Allan 2000). *Figure A.1* in the *Appendix* shows the spatial distribution of regional precipitation anomalies, associated to different *La Niña* events occurred in late summer (September-October). This study will focus on the late-summer rainfall shocks related to the 1998-1999 *La Niña* event.

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; ENSO activity and characteristics appear to be strongly related to the tropical Pacific climate system, which is expected to change during the 21st century in response to climate change (Vecchi and Wittemberg 2009). It is, therefore, of great interest to understand the nature and magnitude of ENSO impacts on society.

2.2 ENSO, weather and agriculture

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 to climatic events of this nature.

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 2008).

This study will focus on the Spring-Summer agricultural season, the most important in terms of production. The agricultural 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.[9] Later, the growing season is vulnerable to lack of rain (FAO 1991). Finally, the harvest season, which is the one we focus on in this study, is sensitive to hurricanes and flooding events (SAGARPA 2008).

Figure 1 shows the rainfall distribution[10] in the area under study for the Spring-Summer agricultural seasons related to the 1997-1998 *El Niño* and 1998-1999 *La Niña* events. We choose to analyze 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. As seen in *Figure 1*, the 1997-1998 *El Niño* was also characterized by droughts at the beginning of the agricultural season. The low variability of rainfall meant that most of the region under study was similarly affected by this shock. Households could react to droughts at the beginning of the agricultural season by shifting resources to other income generating activities, for example, migrating seasonally or permanently (Munshi 2003). On the other end, extreme rainfall shocks at the end of the agricultural season were closer to negative

[9] 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").

[10] The region under study is divided by 0.5 degree x 0.5 degree grids. The graph illustrates the distribution of rainfall standardized deviations from the 1961-1999 historic averages for the different grids.

income shocks given that all the investment of labor and resources had already been spent on the crop. Evidence from the households in the database used suggests that these rainfall shocks were unexpected.[11]

3 Data

3.1 Progresa Data

The data used in this study is part of *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 in a subset of the original villages (in addition to household socioeconomic data). The 2003 dataset includes information for 259 villages, 5,000 households, and 6,264 children on anthropometric, health, cognitive, and gross motor development indicators.[12]

Cognitive tests. The *Peabody Picture Vocabulary Test* (PPVT) and three subsections of the *Batería III Woodcock-Muñoz Test*[13] (WMT) are used as indicators of cognitive development. The PPVT measures the receptive vocabulary of children aged 3 to 6 by asking them to indicate which of four pictures best represents a stimulus word. Studies have found that vocabulary tests tend to be strong predictors of school success and contribute in a large extent on tests that assess general intelligence. The PPVT test is used in preschool aged children to assess early child development (Dunn et al. 1986).

Three subtests of the WMT were used to measure long-term memory, working memory, and visual-spatial thinking for children 2 to 6 years old. These abilities are measured, respectively, by requiring children to: learn associations between unfamiliar auditory and

[11] Households do not report significant effects in change of land used or total area planted at the beginning of the agricultural season when comparing households in regions affected and not affected by the weather shocks used in the analysis.

[12] Data is publicly available at http://evaluacion.oportunidades.gob.mx/evaluacion

[13] The Spanish version of the Woodcock-Johnson test.

visual stimuli; remember and repeat single words, phrases, and sentences; and identify an object's picture from a partial drawing or representation. Schrank et al. (2005) describe these abilities as follows: (i) long-term memory is the ability to store information and fluently retrieve it later; (ii) working memory (also referred to as short-term memory) is the capacity to hold information in immediate awareness while performing a mental operation on the information; and (iii) and visual-spatial thinking is the ability to perceive, analyze, synthesize, and think with visual patterns, including the ability to store and retrieve visual associations. Because of their high *internal reliability* and *validity*,[14] the WMT and the PPVT are regularly selected to evaluate early childhood abilities and have been found to be good predictors of later school achievement (Duncan et al. 2007).

Anthropometric variables. The 2003 *Progresa* follow-up survey also includes objective measures of *height* and *weight* collected by a qualified nurse for all the children in the sample. The binary variable *stunting* is constructed based on the WHO definition: 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 (World Health Organization 1979). *Stunting*, or low weight for age, usually reflects insufficient nutrient intake during early stages of development. It generally occurs before age two and once established, it is usually permanent (most children never gain the height lost nor achieve a normal body weight). Consequences may be extremely severe: a stunted growth may lead to premature death later in life due to incomplete development of vital organs during childhood. Less extreme effects also include delayed development, impaired cognitive function, and poor school performance (UNICEF 2007).

Health indicators. Blood samples were also gathered for all children as part of the 2003 data collection. By using hemoglobin levels, adjusted for village altitude, an indicator for *anemia* is generated based on the World Health Organization standards (Ruiz-Argüelles and Llorente-Peters 1981). *Anemia* is usually an indicator of poor nutrition (mainly iron

[14] 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.).

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 comes from mothers' survey responses. Mothers were asked to report the number of days that their children were sick during the previous month and unable to perform their regular activities. This number corresponds to the variable *days_sick*.

Gross motor skills. 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 1974). Besides school failure, difficulty or inability to perform manual jobs 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 (Polatajko 2005).

The MSCA tests, administered to all children between 2 and 6, focused on leg coordination: the first tests required children to stand on one foot and measured both the ability to perform the task and the amount of time endured staying in balance (in seconds); the second and third tests assessed the ability to walk backwards and to walk straight following a line, respectively.

Table 1 provides descriptive statistics for all the outcomes as well as controls that will be used in the empirical specification.

3.2 Climatic Data

Monthly precipitation data available from the University of East Anglia Climate Research Unit (UEA CRU -TS2p1) is used to measure the presence of rainfall shocks in the region under analysis. The monthly series are available as interpolated gridded data with a spatial resolution of 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 grids. The number of villages per grid varies, from a minimum of 1 to a maximum of 20.

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 variable was constructed using each grid's *standardized precipitation anomaly*. The *standardized precipitation anomaly* indicates the number of standard deviations from the long-term mean (1961-1999) for each grid-month pair. 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). The threshold to identify the weather shocks comes from conversation with climatologists who indicated that this level is already dangerous (destructive) for the crop during the harvest season. Nonetheless, in *section 5*, a sensitivity analysis will consider changing the 0.7 standard deviations cutoff to 0.5 and 1 to assess the relevance of the cutoff point used to define the shock. *Figure 1* shows the monthly distribution of the standardized precipitation anomalies used to define the rainfall shocks.

The use of the *standard precipitation anomalies* to identify the shocks is supported by extensive applications in the climatology literature (Heim 2002; Keyantash and Dracup 2002). 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 indicates substantive loss of crops as a result of floods, therefore, the relation between crop output and rainfall would not be easily fitted with a parametric functional form; and (ii) the use of the binary variable aids the ease of interpretation of the results. Furthermore, the use of different thresholds in the robustness checks informs about the pattern of the results with respect to the *standardized precipitation anomalies.*

4 Empirical Specification

The following specification seeks to identify the medium-term effect of excessive rainfall shocks occurring at early stages of children's development on anthropometric, health, cognitive development and gross motor skill outcomes. The analysis considers children born between 1997 and 2001.

$$Y_{ij} = \left(\sum_{k=1997}^{2001} \gamma_k coh\_k_{ij} + \eta_k rain\_shock_j * coh\_k_{ij} \right) + \beta X_{ij} + \nu_j + \epsilon_{ij} \tag{1}$$

where Y_{ij} is the outcome for individual i in pixel j , coh_k_{ij} is an indicator for individual i in pixel j of being born on year (cohort) k, $rain_j$ is an indicator for a weather shock occurrence in pixel j, X_{ij} are controls for individual i in pixel j, and ν_j gives pixel-clustered standard errors.

Y_{ij} refers to the set of outputs under analysis that include: (i) anthropometric variables, such as weight, height, and stunting; (ii) the logarithm of cognitive test results, which include the Peabody test and three subsections of the Woodcock-Muñoz test; (iii) health indicators, such as *anemia* and self-reported health; and (iv) motor skills coordination results, which include variables from the McCarthy test.

On each estimation, the main parameter of interest will be η_k. Given that the rain shock used for the estimations took place in a specific year (1999), the η_k parameter 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 example, η_{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.

Exogeneity Test. 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. To test the exogeneity assumption of the shocks, the longitudinal feature of the dataset is employed. Using the baseline data from 1997, which corresponds to household's information before the rainfall shock took place, a group of indicators is aggregated at the village level. *Table 2* shows the results from testing the difference of means for several observable indicators extracted from the household's survey.[15] The statistics show that for

[15] The tests were also done using individual level data, and comparing individuals living in localities exposed to the shock with those living in localities not exposed. The same results are derived whether the test uses individual or grid level data.

most observable characteristics there is no difference between villages affected and those not affected by the rainfall shocks at the baseline.

Spatially-correlated standard errors. The estimation of equation 1 adjusts for clustered standard errors by grid. This assumption allows for correlation between observations geographically located in the same grid-cell (i.e. pixel). However, it also assumes that errors of observations located in adjacent grids are independent from each other. In the economic literature, a growing number of studies that use geographical data have adopted an alternative solution that allows for correlation between observations closely located (Dell et al. 2009; Deschenes and Greenstone 2006). The strategy is based on Timothy Conley (1999) work, who proposed a methodology to correct for spatial correlation when estimating the standard errors. Conley's correction consists in allowing the variance-covariance matrix to have correlated standard errors if the observations are located within a pre-specified distance threshold (the threshold has to be assumed).[16] The main estimates in this paper include clustered and spatially correlated standard errors (with 1 decimal degree cutoff assumed). A sensitivity analysis for the standard errors is included in the supplementary material.

5 Results

5.1 Effects on anthropometric and health indicators

Table 3 presents the estimated effects of excessive rainfall shocks 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, *days_sick*).[17]

[16]See Conley (1999) for further details about this methodology. Statistical codes to correct for spatial correlation are also available on Timothy Conley's website.

[17]Similar results were found using as main independent variable the indicator for excessive rainfall shocks occurred in 1998 and can be made available upon request.

Results show significant lower weight and height for children that were exposed during the first two years of life to the shock (0.84 lb. lower weight and 0.71 in. lower height for those born in 1998, and 0.47 in. lower height for those born in 1997) with respect to same-aged children not exposed. Similarly, children born the same year and one year after the shock occurred, exhibit negative effects on height with respect to same-aged children not affected (0.56 in. and 0.43 in., respectively).

The negative impacts on height are substantive enough to significantly increase the probability of stunting. Children born between 1998 and 2001 are significantly more likely to be stunted if they were exposed to the 1999 rainfall shock. The probability of stunting is 14 percentage points higher for children born in 1999 and 2000, and 12 percentage points higher for children born in 1998 and 2001 compared to same-aged children not affected by the shock).

There is no evidence to suggest that anemia and children's number of sick days (reported by their mothers) are significantly affected by the weather shocks.

5.2 Effects on cognitive development

As described on *Section 3*, the 2003 Progresa survey includes several specific cognitive tests: language skills (Peabody Test), long-term memory, short-term memory, and visual-spatial thinking (Woodcock-Muñoz Test). For the estimations, we use as outcomes the logarithm of the test scores.

Table 4 reports the estimated effects of excessive rainfall shocks during the 1999 harvest season on the test scores that measure specific cognitive abilities . The estimates suggest negative and significant effects of the rainfall shocks on language development, long-term memory, and visual-spatial thinking abilities. The larger negative effects are mostly found on children who were affected by the shock during their first or second year of life (i.e. children born in 1997 and 1998). This group of children exhibits 21, 19, and 13 percent lower test scores on the language, long-term, and visual-spatial thinking tests, respectively, with respect to same aged-children not affected by the shock. Lower (in absolute terms), but still significant negative effects are found for children born the year of the shock (1999) or the following year (2000); these negative outcomes range, in absolute value, from 11 to 14 percent. No significant effects were found in short-term memory test scores.

5.3 Effects on gross motor skills

Table 5 shows the effects on gross motor skills measured with outcomes from the *McCarthy Scale of Children's Abilities Tests.* No strong and consistent evidence of negative effects of the shocks is found for these outcomes. Balance is the only outcome for which minor negative effects from the rainfall shocks are found, being the effect on the 1997 cohort the only statistically significant (decrease in 0.7 seconds in the ability to hold balance with one foot).

5.4 Correction for spatially-correlated standard errors

Tables 3, 4, and *5* show the main estimation results calculated with clustered SEs by grid (shown in brackets) and, alternatively, using Conley's proposed corrections for spatial correlation with a 1 decimal degree cutoff (shown in parentheses). As evidenced in the tables, some of the standard errors increase as a result of allowing for spatial correlation, but this increase tends to be small and does not affect the statistical significance of the results. *Table A.1* summarizes three alternatives for the calculation of the standard errors: clustered by pixels, and two estimates of Conley SEs using 1 and 2 decimal degrees thresholds, respectively. The standard errors for the anthropometric estimations are the most sensitive to spatial correlation correction, but overall, the significance of the results remains.

5.5 Persistent effects of the shock

Exposure to weather shocks can have not only immediate impacts on children's life conditions, but also persistent effects over multiple years, such as an extended reduction of income and consumption. *Section 6* will investigate some of the mechanisms that might be contributing to the negative effects on children's cognitive and anthropometric indicators. That section will provide further evidence of the prolonged effects that the shocks had on these mechanisms.

Results for both anthropometric and cognitive outcomes indicate that children in their first or second year of life at the time of the shock were more severely affected. However, this does not necessarily mean that the shock had stronger effects if exposure occurred in early childhood rather than in-utero. Given the persistent effects of the shocks on some of the mechanisms, this could also mean that these chidlren were exposed to the shock for a longer period of time. Similarly, estimates in *tables 3* and *4*, suggesting that children born one year after the shock (in 2000) are negatively affected, could also result from negative conditions in-utero and shortly after birth.

5.6 Robustness checks

Adding controls from the exogeneity test. As discussed in *Section 4*, the empirical specification of this study is based on the assumption that the rain shock is exogenous. The evidence presented in *Table 2* supports this hypothesis. As a robustness test, the few variables that presented significant differences in means in *Table 2*[18] are added to the estimation. If the initial estimates presented 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.2, A.3,* and *A.4* show that the main estimates do not change significantly when these additional controls are added.

Sensitivity analysis for different weather shock cutoffs. A second robustness test consisted on varying the threshold value used to define the rain shock variable ($rain\_shock$). For this sensitivity test we adopted two additional cutoff points: 0.5 and 1 standard deviation. *Tables A.5, A.6* and *A.7* suggest that both thresholds – using 0.5 and 1 standard deviations to define the shock – yield similar results to the original estimates. Adopting the lower 0.5 threshold, produces larger significant coefficients; the reverse is observed when the more stringent cutoff of 1 standard deviation is employed. These results suggest that lower precipitation anomalies are enough to negatively affect children. When the

[18]The household characteristics presenting significantly different means are: (i) TV, (ii) vehicle, and (iii) poultry ownership, (iv) household with permanent migrants at the U.S., (v) an indicator for household head speaking an indigenous language, and (vi) an indicator for household head speaking both Spanish and an indigenous language.

1 standard deviation cutoff is adopted, some children that were actually exposed to the shock, are erroneously included in the control group, yielding a lower estimate for the shock.

6 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 cognitive development and anthropometric outcomes. To do this, 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. We adopt the model described in equation 1 to estimate the effect of the rainfall shock on these 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.

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, $t+1$, $t+2$: from about 40% decline in period t to 26% in period $t+2$. Results for income from agricultural activities are comparable: from about 28% decline in period t to 18% in period $t+2$.

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 5% immediately after the shock for households living in affected villages. Nevertheless, the government aid did 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. From the data available it is possible to see if there was a response to the shocks in terms of family or neighbor related transfers. The results show no significant changes in the probability of receiving informal transfers from family members immediately after the shock. However, we do observe a significant decrease of 3% in the probability of receiving transfers from neighbors. Weakening of intra-village transfers may be explained by the fact that neighbors were also exposed to the rain shock.

Consumption and diet composition. The negative effect on income, paired with absence of formal insurance and credit markets, and the weakening of informal safety nets (e.g. 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 (10% on t, 11% on $t+1$, and 15% on $t+2$) for households exposed to rainfall shocks with respect to those not exposed. These estimates confirm the results found by Vicarelli (2011) using data for all the Progresa villages (506) included in the pilot phase.

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[19] increased immediately after the shock (13%), but later decreased

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

in period $t+2$ (22%). Second, consumption of animal-origin products decreased in periods $t+1$ and $t+2$ by 14% and 17%, respectively. Lastly, consumption of fruit and vegetables decreased by 20% in period t and 14% in period $t+2$. This shift towards cheaper foods, 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 and development of young children.

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 medicine expenditures decreased for households exposed to shocks by 36% in period t and 30% in period $t+1$. Nonetheless, results for medicine expenditure are very likely to be driven by liquidity constraints rather than changes in health status.

7 The Role of Progresa

In 1997, villages in the region under analysis were selected to be included in a governmental conditional cash transfer (CCT) program, called *Progresa*. This section describes the program and investigates its potential mitigating effects against the negative consequences of exposure to the rainfall shock for households eligible to receive the program.

7.1 Brief Progresa's Background

Progresa, now called *Oportunidades*, is a conditional cash transfer program initiated in 1997 by the Mexican government. Nowadays, it is Mexico's most comprehensive and extensive poverty alleviation program with a 5.6 million households' coverage (SEDESOL 2011). Its purpose is to break the intergenerational cycle of poverty through a combination of health and education interventions. The delivery of the cash transfers is conditional on children's school attendance, as well as periodic health check-ups of all family members. The amounts of the transfers vary mainly by the number, age, and gender of the children at school age. Up to date, households receive on average US$588 per year, which corresponds to 0.6 times the amount an individual would earn working for a minimum salary and 0.36 times what the fifth decile household earns.

By design, the intervention 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). The identification strategy of eligible households occurred in three stages. First, 506 poor rural communities from seven different states were selected for the sample. These localities were identified in the 1990 and 1995 Censuses as highly marginalized rural communities[20] with at least fifty households and access to both education and health services. Second, within each community, a baseline socioeconomic survey ENCASEH (Encuesta de Características Socioeconómicas de los Hogares) was administered to all households on November 1997. This information was used to construct a *poverty index* for each household based on its asset ownership and socio-economic characteristics of its members. Eligibility for the program was determined based on this index and a pre-determined threshold. Third, localities in the sample were randomly assigned to either the treatment (320) or control group (186). 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)

7.2 Empirical identification of Progresa's effects

Randomized Experiment. Most of the previous work related to *Progresa* has taken advantage of the randomization aspect of it. Behrman and Todd (2000) showed that several

[20]Marginalization was defined using a pre-determined locality-level index generated every five years by the Mexican Ministry of Population. This index combines several locality's characteristics. Rural communities are defined as those below 2,500 inhabitants.

basic variables such as age, gender, income, and schooling are balanced when comparing households in control and treatment localities. The first empirical estimation used here to assess the potential mitigating effects of *Progresa* follows the line of randomized control trial's estimations:

$$Y_j = \eta_1 rain\_shock_j + \eta_2 Treat_j + \eta_3 rain\_shock_j * Treat_j + \epsilon_j \tag{2}$$

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

In the specification, η_2 represents the effect of the early treatment on the outcomes at villages not exposed to rain shocks, and $\eta_2 + \eta_3$ represents the effect of the early treatment in villages affected by the 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. Therefore, the randomization makes possible to identify early versus late treatment effects, rather than the more traditional treatment versus control effect.

Regression Discontinuity (RD). To implement a regression discontinuity design, 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 variables used to generate the poverty index, and the cutoff value to select beneficiaries. A standardized poverty index (x_pmt_j) is formed by subtracting the regional cutoff to the each household's poverty index. Therefore, independently of the region, a household would be eligible for the program if its standardized poverty index is above zero ($x\_pmt_j > 0$).

The main assumption behind the RD strategy is that, other than the treatment benefits, the households around the cutoff value 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).[21]

[21] To assess the effectiveness of the RD method, the authors estimated the effect of *Progresa* on school

RD methods can employ both, parametric and non-parametric estimators. However, the best way to illustrate the RD is with graphical analysis. We organized the analysis in two parts:

1. First Stage: we begin by showing the discontinuity of *Progresa's* beneficiaries at the administrative cutoff. We use the sample to estimate: $E(Benef_j|x\_pmt_j)$, where $Benef_j$ is a dummy variable equal to one if household j is a *Progresa* beneficiary. If targeting of the program and compliance were perfect we would expect to have a sharp RD.

2. Reduced Form: we show the conditional means of the outcome variables with respect to the standardized poverty index $[E(Outcome_{ij}|x\_pmt_j)]$. Any discrete jump at the cutoff value is attributed to the treatment. To estimate the potential mitigating effects of *Progresa* against the weather shocks, this analysis is performed for two subsamples: those observations living in villages affected by the rain shocks, and those not.

7.3 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.[22]

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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).

[22] Similar results are obtained if the estimates are calculated at the household level.

In previous work, Fernald and Gertler (2004) find positive effects from *Progresa* on anthropometric outcomes when comparing children in experimental villages to children from a synthetic control (formed from villages that by 2003 were still not receiving *Progresa's* benefits).[23] Moreover, as in these estimates, they don't find 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. The key assumption behind their main results is that the synthetic control villages had to be similar to the experimental villages in 1997. However, this is a strong assumption given that *Progresa* targeted the most disadvantaged localities by design. By the beginning of 2003, *Progresa* had geographical presence in 2,354 municipalities (97% of Mexico's total municipalities).

Rather than following this approach, this paper exploits the rule that determines household eligibility based on the poverty index and the pre-determined cutoffs. This gives the ideal setup for a regression discontinuity analysis.

Regression Discontinuity. *Figures 2* to *4* show the main results form the RD analysis. The first set of graphs (*Figure 2*) show the First Stage results described in *Section 7.2*, 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 the lack of discontinuity in 2002.

The analysis is restricted to treatment localities. If control localities were added, the shape of the graphs in *Figure 2* 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

[23] The synthetic control was selected using matching estimators.

give the difference between receiving the treatment from 1998 rather than from 2002 at the discontinuity point. Given that the outcomes analyzed on this paper were measured in 2003, we believe that the RD approach should allow a better identification of the *Progresa* effects. This approach gives a lower time window for households that receive the benefits later to catch-up with those that received them form the beginning of the program. Also, the RD assumptions are less restrictive than those required to use *Progresa's* 2003 synthetic control.[24]

Figure 3 illustrates the result of the RD analysis for two anthropometric outcomes: weight and height. Similarly, *Figure 4* gives two examples using cognitive outcomes: language (PPVT test) and long-term memory (Woodcock-Muñoz test). The triangles (circles) in the graphs represent the conditional means for those children that were (not) affected early on childhood by the ENSO-related shocks. The RD graphical analysis for the rest of the anthropometric, health and cognitive outcomes is included in *Figures A2* and *A3* in the supplementary material. The difference in the level of the means for the two subgroups reflects the negative effect of the shock, which is consistent with *Section's 5* analysis. However, *Progresa* does not seem to provide mitigation effects against the shocks (nor even direct effects on the outcomes).

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 point. However, the positive changes on these indicators do not allow for a mitigation of the negative effects of the rain shocks.[25] Other possible explanation for a lack of mitigation evidence includes differences in 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

[24] As described previously, Fernald and Gertler (2004) use the 2003 synthetic control. Also, several other *Progresa* medium-term evaluations adopted the 2003 synthetic cohort approach.

[25] Graphs can be made available upon request.

increased, while adult's consumption wasn't reported to be greatly affected. In the case of *Progresa* there is also a higher incentive to 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 (Eccleston 2011; Kaiser and Sachser 2005).

It is important to indicate that a limitation associated with the RD estimates is that it provides a Local Average Treatment Effect (i.e. the effect of the treatment around the cutoff level). If the treatment has heterogenous effects along the income distribution, then this result cannot be generalized to the rest of the population. It could be argued that the effects of *Progresa* are stronger for the poorest populations. However, given the sample characteristics and *Progresa's* design to target the poor, it would be expected that the group around the cutoff to be already representative of poor (although not extreme) Mexican rural households.

8 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.

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Table 1: Descriptive statistics

Variable	Num. obs	Mean	Std. Dev.	Min	Max
Anthropometrics and health					
weight (lb)	6233	33.33	6.6580	16.31	122.14
height (in)	6209	37.93	3.5430	16.81	56.54
stunting (binary)	4684	0.38	0.4842	0	1
anemia (binary)	6215	0.27	0.4415	0	1
sick days	5598	1.39	2.7874	0	30
Cognitive tests					
language (Peabody)	4671	2.25	0.8946	0	4.37
LT memory (WM 1)	6010	2.17	0.8818	0	4.17
ST memory (WM 2)	5747	2.95	0.6293	0	4.01
visual-spatial (WM 3)	4988	2.30	0.5959	0	3.74
Motor skills					
balance (seconds)	5943	8.29	5.0580	0	45
walk back (binary)	6088	0.89	0.3180	0	1
walk str (binary)	6041	0.83	0.3735	0	1
Controls					
age (months)	8173	50.26	16.44	19	82
male (binary)	8173	0.51	0.50	0	1
HH Poverty index (1997)	5254	703.06	134.67	237	1239
HH size (1997)	5268	6.08	2.56	1	24
HH head language					
* spanish & indigenous	5281	0.4	0.49	0	1
* only indigenous	5281	0.04	0.18	0	1

Continued on next page

Table 1 − continued

Variable	Num. obs	Mean	Std. Dev.	Min	Max
Distribution of birth cohorts					
coh97	8173	0.17	0.3793	0	1
coh98	8173	0.21	0.4099	0	1
coh99	8173	0.22	0.4128	0	1
coh00	8173	0.21	0.4085	0	1
coh01	8173	0.18	0.3863	0	1
Shocks by birth cohort					
coh97*rain_shock	8173	0.11	0.3110	0	1
coh98*rain_shock	8173	0.13	0.3351	0	1
coh99*rain_shock	8173	0.13	0.3388	0	1
coh00*rain_shock	8173	0.13	0.3341	0	1
coh01*rain_shock	8173	0.11	0.3186	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 $rain\_shock_j = 0$	Mean $rain\_shock_j = 1$	Difference	t-statistic
	(1)	(2)	(3)	(4)
Village characteristics				
male avg. wages	318.3	303.2	15.17	1.248
female avg. wages	41.81	45.44	-3.629	-0.980
Household characteristics and assets				
size	6.748	6.827	-0.0792	-0.683
Poverty index	712.7	705.5	7.189	0.670
owns land (ha)	1.749	1.727	0.0215	0.128
own house (binary)	0.940	0.936	0.00387	0.338
electricity (binary)	0.776	0.761	0.0154	0.373
water (binary)	0.0395	0.0448	-0.00533	-0.567
tv (binary)	0.617	0.471	0.147***	4.360
vehicle (binary)	0.136	0.0599	0.0764***	4.615
donkeys	0.421	0.384	0.0371	0.691
bullocks	0.130	0.129	0.000910	0.0158
sheep	1.695	1.606	0.0888	0.234
chickens	6.719	7.933	-1.213**	-2.666
pigs	1.151	1.322	-0.171	-1.160

Continued on next page

Table 2 – continued

	Mean $rain\_shock_j = 0$	Mean $rain\_shock_j = 1$	Difference	t-statistic
Household migratory characteristics				
temporary migrants	0.0463	0.0392	0.00715	1.407
permanent migrants to:				
US	0.0392	0.0119	0.0274*	2.548
Mexico	0.0236	0.0221	0.00151	0.186
Head of household characteristics				
male (binary)	0.904	0.889	0.0147	1.199
age (years)	43.11	41.79	1.319	1.965
education (years)	3.759	3.597	0.162	1.028
agric worker	0.701	0.738	-0.0373	-1.386
language spoken:				
Indigenous	0.00681	0.0357	-0.0289***	-3.469
Spanish & Indigen.	0.177	0.397	-0.220***	-4.704

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

Table 3: Effect of the 1999 September-October rainfall shock on anthropometric indicators measured in 2003 for children born between 1997 and 2001.

	weight (lb)[a]	height (in)[a]	stunting[b]	anemia[c]	days_sick[d]
	(1)	(2)	(3)	(4)	(5)
coh97 x rain_shock[e]	-0.613	-0.466**	.	-0.0323	0.346
	[0.6137]	[0.2190]	.	[0.0624]	[0.2652]
	(0.6565)	(0.2629)		(0.6)	(0.2421)
coh98 x rain_shock	-0.837*	-0.709***	0.127*	-0.0132	0.00235
	[0.4806]	[0.2176]	[0.0722]	[0.0336]	[0.1813]
	(0.5352)	(0.2475)	(0.0712)	(0.0394)	(0.1781)
coh99 x rain_shock	-0.733	-0.555**	0.140**	0.00325	-0.232
	[0.4399]	[0.2483]	[0.0672]	[0.0368]	[0.1860]
	(0.4924)	(0.2826)	(0.0720)	(0.0364)	(0.2170)
coh00 x rain_shock	-0.145	-0.426*	0.140**	0.00877	-0.00481
	[0.3484]	[0.2485]	[0.0630]	[0.0338]	[0.2043]
	(0.3378)	(0.2514)	(0.0658)	(0.0368)	(0.2007)
coh01 x rain_shock	-0.468	-0.189	0.115*	0.00671	0.0899
	[0.3742]	[0.2052]	[0.0653]	[0.0616]	[0.2517]
	(0.3991)	(0.1867)	(0.073)	(0.0716)	(0.2211)
Observations	3729	3705	2777	3765	3377
R^2	0.58	0.76	0.09	0.03	0.02
Mean	33.42	38.08	0.384	0.273	1.282

Controlling for age (months), age^2, gender, father's language, HH structure, cohorts, poverty index (1997).

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

Standard errors clustered by grid in brakets; Conley standard errors in parentheses (cutoff= 1 degree).

[a] Weight and height are measures in pounds and inches, respectively.

[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 of a healthy reference population [World Health Organization, 1979].

[c] Anemia is a binary variable = 1 if the child is anemic. Anemia is defined as hemoglobin less than 11 g/dL adjusted for altitude using standard adjustments (Guillermo Jose Ruiz-Arguelles and Antonio Llorente-Peters 1981; Gertler 2004].

[d] Number of days in the previous 4 weeks that the child was reported sick by the mother.

[e] *coh97 x rain_shock* indicates the interaction between the variable *coh97* (=1 if the child was born in 1997) and the variable *rain_shock* (=1 if a rainfall shock occurred in 1999).

Table 4: Effect of the 1999 September-October rainfall shock on cognitive development indicators measured in 2003 for children born between 1997 and 2001. (Outcomes are the logarithm of test scores).

	Peabody Test[a]	**Woodcock-Muñoz Test**[b]		
	language	long term memory	short term memory	visual-spatial thinking
	(1)	(2)	(3)	(4)
coh97 x rain_shock[c]	-0.216**	-0.194*	-0.000168	-0.133***
	[0.0967]	[0.1042]	[0.0257]	[0.0424]
	(0.1055)	(0.1199)	(0.0288)	(0.0496)
coh98 x rain_shock	-0.209***	-0.199***	0.0139	-0.121***
	[0.0601]	[0.0644]	[0.0322]	[0.0335]
	(0.0679)	(0.0817)	(0.0363)	(0.0398)
coh99 x rain_shock	-0.148**	-0.162***	-0.0532	-0.111**
	[0.0682]	[0.0598]	[0.0370]	[0.0493]
	(0.0651)	(0.0649)	(0.0357)	(0.058)
coh00 x rain_shock	-0.0258	-0.147**	0.0173	-0.143**
	[0.0672]	[0.0568]	[0.0374]	[0.0541]
	(0.0576)	(0.0565)	(0.0356)	(0.0486)
coh01 x rain_shock	-0.225	-0.0300	-0.0755	0.0364
	[0.6933]	[0.0549]	[0.0552]	[0.0899]
	(0.6910)	(0.66)	(0.0493)	(0.1003)
Observations	2835	3522	3385	2967
R^2	0.33	0.32	0.48	0.38

Controlling for age (months), age^2, gender, father's language, HH structure, cohorts, poverty index (1997).

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

Standard errors clustered by grid in brakets; Conley standard errors in parentheses (cutoff= 1 degree).

[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 wide range of cognitive abilities: long-term memory, short-term memory and visual spatial thinking.

[c] *coh97 x rain_shock* indicates the interaction between the variable *coh97* (=1 if the child was born in 1997) and the variable *rain_shock* (=1 if a rainfall shock occurred in 1999).

Table 5: Effect of the 1999 September-October rainfall shock on gross motor skills measured in 2003 for children born between 1997 and 2001. These gross motor skills are central to the successful performance of school tasks.

	balance (seconds)[a]	ability to walk backward[b]	ability to walk straight[b]
	(1)	(2)	(3)
coh97 x rain_shock[c]	-0.718**	0.0228	0.0140
	[0.3420]	[0.0162]	[0.0117]
	(0.3686)	(0.0186)	(0.0109)
coh98 x rain_shock	-0.164	0.0136	0.0220*
	[0.2609]	[0.0130]	[0.0118]
	(0.2628)	(0.0119)	(0.0104)
coh99 x rain_shock	-0.357	0.0174	-0.0371**
	[0.3408]	[0.0155]	[0.0156]
	(0.3452)	(0.0152)	(0.0134)
coh00 x rain_shock	-0.210	-0.0216	-0.00701
	[0.3739]	[0.0283]	[0.0374]
	(0.2811)	(0.0246)	(0.0351)
coh01 x rain_shock	0.0831	-0.0308	-0.0514
	[0.4352]	[0.0563]	[0.0509]
	(0.3796)	(0502)	(0.0488)
Observations	3563	3693	3663
R^2	0.33	0.16	0.24
Mean	8.286	0.891	0.843

Controlling for age (months), age^2, gender, father's language, HH structure, cohorts, poverty index (1997).

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

Standard errors clustered by grid in brakets; Conley standard errors in parentheses (cutoff= 1 degree).

[a] The child's ability to keep her/his balance on one foot is measured in seconds.

[b] The binary variables = 1 if the child was able to successfully complete the task.

[c] *coh97 x rain_shock* indicates the interaction between the variable *coh97* (=1 if the child was born in 1997) and the variable *rain_shock* (=1 if a rainfall shock occurred in 1999).

Table 6: Effect of rainfall shocks on income at different periods t, t+1, and t+2; as well as on the probability of receiving formal and informal transfers immediately after the shock. 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 (✓)	Coefficient[a]	Std_Dev
Total household income (log)			
$income_t$		-0.395***	(0.052)
$income_{t+1}$		-0.291***	(0.052)
$income_{t+2}$		-0.263***	(0.042)
Household income from agriculture (log)			
$agricultural\_income_t$		-0.276***	(0.047)
$agricultural\_income_{t+1}$		-0.268***	(0.056)
$agricultural\_income_{t+2}$		-0.181***	(0.044)
=1 if household received government aid			
$food\_aid_t$	✓	0.047**	(0.021)
$other\_aid_t$	✓	0.006	(0.034)
=1 if household received informal transfers			
$from\_family_t$	✓	-0.042	(0.043)
$from\_neighbor_t$	✓	-0.028***	(0.009)

Standard errors clustered by gridcell [in brackets].

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

[a] Each line shows the result of separate regressions. Control variables for each model include: (i) household's head characteristics (age, male, years of education, language, sector of employment, marital status); (ii) household characteristics (size, structure, baseline poverty index in 1997); and (iii) village characteristics (average male and female wage).

Table 7: Effect of rainfall shocks on food consumption, diet composition, child health, and medicine expenditures. All responses are estimated up to two years (t, $t+1$, $t+2$) after exposure to the shock.

Dependent Variables	Coefficient[a]	Std_Dev
Food consumption (log)		
$food\_consumption_t$ [pesos]	-0.100***	(0.035)
$food\_consumption_{t+1}$ [pesos]	-0.115***	(0.034)
$food\_consumption_{t+2}$ [pesos]	-0.149***	(0.055)
$food\_consumption_t$ [kg]	-0.027	(0.036)
$food\_consumption_{t+1}$ [kg]	0.003	(0.030)
$food\_consumption_{t+2}$ [kg]	0.042	(0.057)
Diet composition (log)		
$tortilla\_consumption_t$ [pesos]	0.132**	(0.054)
$tortilla\_consumption_{t+1}$ [pesos]	-0.085	(0.064)
$tortilla\_consumption_{t+2}$ [pesos]	-0.218***	(0.069)
$animal\_consumption_t$ [pesos]	-0.052	(0.085)
$animal\_consumption_{t+1}$ [pesos]	-0.145*	(0.075)
$animal\_consumption_{t+2}$ [pesos]	-0.171**	(0.076)
$fruit\_and\_vegetable\_consumption_t$ [pesos]	-0.200***	(0.057)
$fruit\_and\_vegetable\_consumption_{t+1}$ [pesos]	-0.078	(0.049)
$fruit\_and\_vegetable\_consumption_{t+2}$ [pesos]	-0.143**	(0.056)
Children reported sick by the mother		
$children\_sick_t$ (% in the HH)	0.011	(0.022)
$children\_sick_{t+1}$ (% in the HH)	0.025	(0.027)
$children\_sick_{t+2}$ (% in the HH)	0.016	(0.031)
Medicine Expenditure (log)		
$medicine\_expenditures_t$	-0.361***	(0.121)
$medicine\_expenditures_{t+1}$	-0.303**	(0.113)
$medicine\_expenditures_{t+2}$	0.043	(0.128)

Standard errors clustered by gridcell [in brackets]. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[a] Each line shows the result of separate regressions. Control variables for each model include: (i) household's head characteristics (age, male, years of education, language, sector of employment, marital status); (ii) household characteristics (size, structure, baseline poverty index in 1997); and (iii) village characteristics (average male and female wage).

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 2). Outcomes in this model correspond to village level means of individual observations.

Anthropometric and Health Indicators

	weight (lb) (1)	height (in) (2)	Stunting (3)	Anemia (4)	Days_sick (5)
Rain shock[a]	-0.516	-0.467**	0.126***	0.0297	0.0847
	[0.4104]	[0.2298]	[0.0357]	[0.0254]	[0.1768]
Treatment[b]	-0.181	-0.0598	0.0118	0.0510*	-0.0997
	[0.4066]	[0.2182]	[0.0303]	[0.0307]	[0.1689]
Treatment x Rain shock	-0.702	-0.255	0.00271	-0.0407	0.0485
	[0.5705]	[0.3153]	[0.0505]	[0.0374]	[0.2321]
Observations[c]	259	259	259	258	259
R^2	0.06	0.06	0.09	0.01	0.01
Mean	33.92	38.29	0.301	0.261	1.380

Cognitive Development Indicators

	Peabody Test	**Woodcock-Muñoz Test**		
	language (1)	long term memory (2)	short term memory (3)	visual-spatial thinking (4)
Rain shock[a]	-0.159**	-0.137**	-0.100**	-0.139***
	[0.0762]	[0.0684]	[0.0406]	[0.0439]
Treatment[b]	0.0330	-0.00983	-0.0419	-0.0459
	[0.0724]	[0.0650]	[0.0402]	[0.0452]
Treatment x Rain shock	-0.0197	-0.0463	0.0592	0.0466
	[0.0976]	[0.0864]	[0.0556]	[0.0606]
Observations[c]	253	259	259	259
R^2	0.05	0.06	0.03	0.06

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] $Treatment$ randomly defined at the village level.

[c] Outcomes are village level means of individual observations.

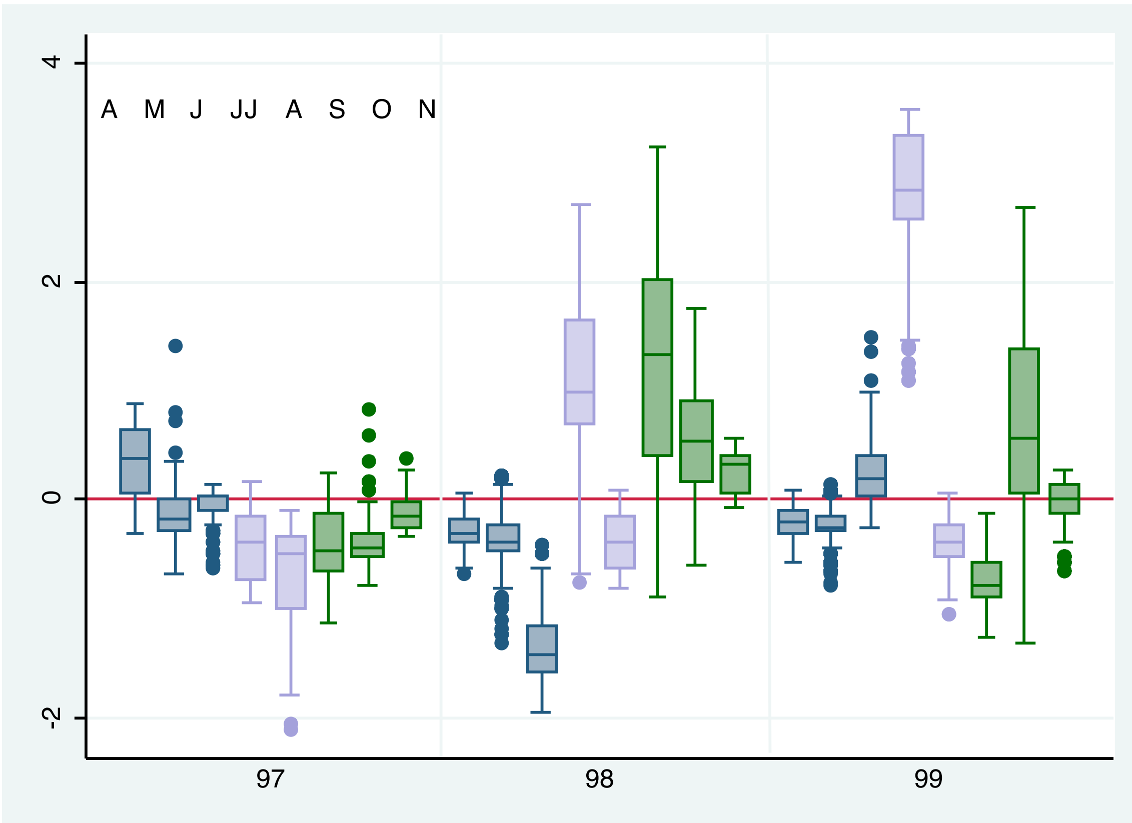


Figure 1: Distribution of Monthly Precipitation Standardized Anomalies.

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.

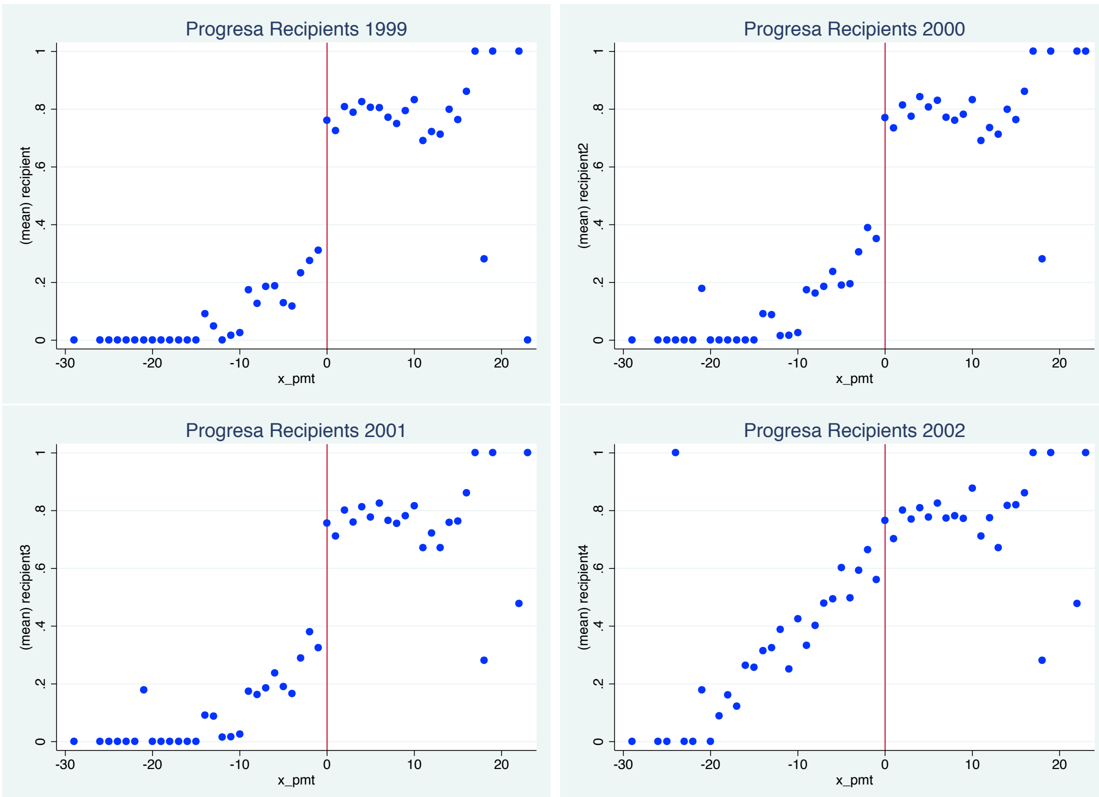


Figure 2: Regression Discontinuity: First Stage ID

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

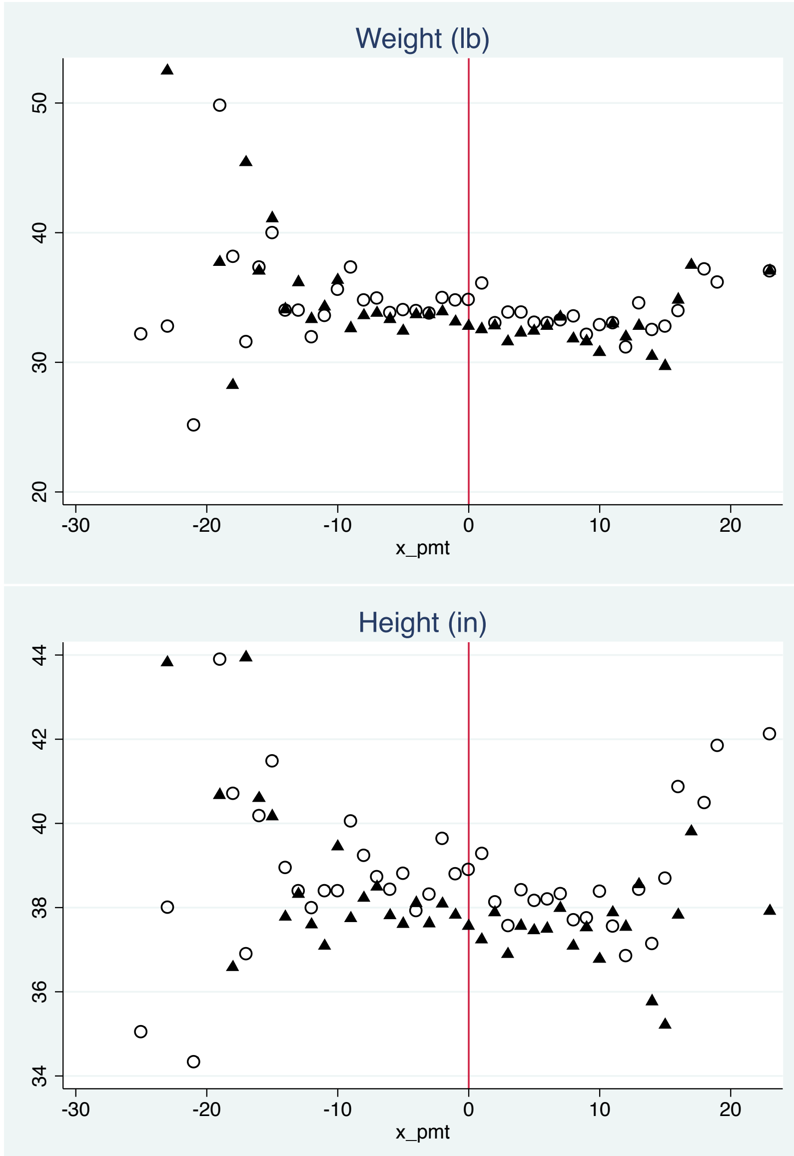


Figure 3: Regression Discontinuity Analysis: Anthropometric Outcomes

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 conditional means of the individual outcomes. ▲is the conditional mean for individuals from villages affected by a rain shock. ○is the conditional mean for individuals from villages not affected by a rain shock.

Figure 4: Regression Discontinuity Analysis: Cognitive Outcomes

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 conditional means of the individual outcomes. ▲is the conditional mean for individuals from villages affected by a rain shock. ○is the conditional mean for individuals from villages not affected by a rain shock.

Table A.1: Summary of Conley SEs.

						Peabody Test	Woodcock-Muñoz Test			Motor Skills		
	weight (lb)	height (in)	stunting	anemia	days_sick	language	long term memory	short term memory	visual-spatial thinking	balance (seconds)	ability to walk backward	ability to walk straight
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
coh97 x rain_shock	[0.6137]	[0.2190]	.	[0.0624]	[0.2652]	[0.0967]	[0.1042]	[0.0257]	[0.0424]	[0.3420]	[0.0162]	[0.0117]
	(0.6565)	(0.2629)		(0.6)	(0.2421)	(0.1055)	(0.1199)	(0.0288)	(0.0496)	(0.3686)	(0.0186)	(0.0109)
	(0.6192)	0.2881		0.0571	0.2301	0.12	0.1187	0.0287	0.0516	0.3064	0.0208	0.0097
coh98 x rain_shock	[0.4806]	[0.2176]	[0.0722]	[0.0336]	[0.1813]	[0.0601]	[0.0644]	[0.0322]	[0.0335]	[0.2609]	[0.0130]	[0.0118]
	(0.5352)	(0.2475)	(0.0712)	(0.0394)	(0.1781)	(0.0679)	(0.0817)	(0.0363)	(0.0398)	(0.2628)	(0.0119)	(0.0104)
	0.6177	0.2974	0.0709	0.0393	0.1607	0.0721	0.0907	0.0382	0.0403	0.2292	0.0118	0.0081
coh99 x rain_shock	[0.4399]	[0.2483]	[0.0672]	[0.0368]	[0.1860]	[0.0682]	[0.0598]	[0.0370]	[0.0493]	[0.3408]	[0.0155]	[0.0156]
	(0.4924)	(0.2826)	(0.0720)	(0.0364)	(0.2170)	(0.0651)	(0.0649)	(0.0357)	(0.058)	(0.3452)	(0.0152)	(0.0134)
	0.5619	0.3272	0.0806	0.0343	0.1896	0.0612	0.0735	0.0345	0.0592	0.3557	0.0156	0.0135
coh00 x rain_shock	[0.3484]	[0.2485]	[0.0630]	[0.0338]	[0.2043]	[0.0672]	[0.0568]	[0.0374]	[0.0541]	[0.3739]	[0.0283]	[0.0374]
	(0.3378)	(0.2514)	(0.0658)	(0.0368)	(0.2007)	(0.0576)	(0.0565)	(0.0356)	(0.0486)	(0.2811)	(0.0246)	(0.0351)
	0.3627	0.2852	0.0725	0.036	0.1745	0.046	0.0502	0.0381	0.0423	0.2735	0.0236	0.0353
coh01 x rain_shock	[0.3742]	[0.2052]	[0.0653]	[0.0616]	[0.2517]	[0.6933]	[0.0549]	[0.0552]	[0.0899]	[0.4352]	[0.0563]	[0.0509]
	(0.3991)	(0.1867)	(0.073)	(0.0716)	(0.2211)	(0.6910)	(0.066)	(0.0493)	(0.1003)	(0.3796)	(0502)	(0.0488)
	0.3959	0.1946	0.0844	0.0751	0.1998	0.6822	0.0651	0.0388	0.0944	0.3306	0.0432	0.0536

Robust standard errors clustered by pixel are reported in brackets; Conley SEs, with cutoff=1decimal deg, are reported in parentheses; and the remaining figures are Conley standard errors with cutoff=2 decimal deg.

Table A.2: Robustness check: Effect of the 1999 September-October rainfall shock on anthropometric and health outcomes controlling for variables that show significant differences in the exogeneity test

	weight (lb)	height (in)	Stunting	Anemia	Days_sick
	(1)	(2)	(3)	(4)	(5)
coh97 x rain_shock	-0.497	-0.448**	.	-0.0369	0.403
	[0.6128]	[0.2179]	.	[0.0614]	[0.2723]
coh98 x rain_shock	-0.715	-0.687***	0.129*	-0.0160	0.0306
	[0.4672]	[0.2067]	[0.0711]	[0.0332]	[0.1789]
coh99 x rain_shock	-0.651	-0.507**	0.126**	-0.000984	-0.222
	[0.4071]	[0.2297]	[0.0629]	[0.0362]	[0.1749]
coh00 x rain_shock	-0.103	-0.401*	0.135**	0.00612	0.0250
	[0.3290]	[0.2381]	[0.0598]	[0.0338]	[0.2064]
coh01 x rain_shock	-0.357	-0.140	0.103	0.00328	0.127
	[0.3509]	[0.1873]	[0.0619]	[0.0615]	[0.2529]
Observations	3730	3706	2776	3764	3376
R^2	0.58	0.76	0.10	0.03	0.02
Mean	33.42	38.10	0.384	0.273	1.282

rain_shock=1 if child was present in a village with a flood occurrence in 1999

Standard errors clustered by gridcell [in brackets]. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Additional controls: TV and vehicle ownership, chickens owned, permanent migrants to the U.S.

Table A.3: Robustness check: Effect of the 1999 September-October rainfall shock on cognitive development outcomes controlling for variables that show significant differences in the exogeneity test

	Peabody Test	**Woodcock-Muñoz Test**		
	language	long term memory	short term memory	visual-spatial thinking
	(1)	(2)	(3)	(4)
coh97 x rain_shock	-0.199**	-0.175*	0.00643	-0.123***
	[0.0963]	[0.1015]	[0.0252]	[0.0420]
coh98 x rain_shock	-0.196***	-0.189***	0.0185	-0.115***
	[0.0566]	[0.0605]	[0.0312]	[0.0307]
coh99 x rain_shock	-0.125*	-0.141**	-0.0467	-0.101**
	[0.0673]	[0.0580]	[0.0364]	[0.0459]
coh00 x rain_shock	-0.00328	-0.133**	0.0223	-0.132**
	[0.0654]	[0.0575]	[0.0368]	[0.0519]
coh01 x rain_shock	-0.225	-0.0168	-0.0686	0.0489
	[0.6753]	[0.0524]	[0.0552]	[0.0911]
Observations	2840	3521	3384	2966
R^2	0.34	0.32	0.48	0.39

rain_shock=1 if child was present in a village with a flood occurrence in 1999

Standard errors clustered by gridcell [in brackets]. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Additional controls: TV and vehicle ownership, chickens owned, permanent migrants to the U.S

Table A.4: Robustness check: Effect of the 1999 September-October rainfall shock on gross motor skill outcomes controlling for variables that show significant differences in the exogeneity test

	balance (seconds) (1)	ability to walk backward (2)	ability to walk straight (3)
coh97 x rain_shock	-0.646*	0.0264	0.0154
	[0.3285]	[0.0162]	[0.0120]
coh98 x rain_shock	-0.124	0.0154	0.0235*
	[0.2588]	[0.0132]	[0.0123]
coh99 x rain_shock	-0.289	0.0186	-0.0343**
	[0.3319]	[0.0155]	[0.0155]
coh00 x rain_shock	-0.169	-0.0194	-0.00535
	[0.3763]	[0.0287]	[0.0378]
coh01 x rain_shock	0.157	-0.0295	-0.0486
	[0.4289]	[0.0561]	[0.0514]
Observations	3562	3692	3662
R^2	0.33	0.16	0.24
Mean	8.286	0.891	0.843

rain_shock=1 if child was present in a village with a flood occurrence in 1999

Standard errors clustered by gridcell [in brackets]. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Additional controls: TV and vehicle ownership, chickens owned, permanent migrants to the U.S

Table A.5: Sensitivity tests: analysis presented in table 3 are reproduced here using rainfall variables corresponding to two different cutoff points (standardized precipitation anomalies higher than 1 and 0.5 standard deviations, respectively). As in table 3, this table presents the effect of the 1999 September-October rainfall shock on anthropometric indicators measured in 2003 for children born between 1997 and 2001: weight measured in pounds; height measured in inches, stunting, anemia, and number of sick days.

	weight (lb)[a]	height (in)[a]	stunting[b]	anemia[c]	days_sick[d]
	(1)	(2)	(3)	(4)	(5)
rain_shock= 1 if standardized precipitation anomaly> 0.5					
coh97 x rain_shock[e]	-1.823***	-0.787***	.	0.0615	0.256
	[0.6116]	[0.2294]	.	[0.0604]	[0.2864]
coh98 x rain_shock	-0.932*	-0.718***	0.113	0.0276	0.00733
	[0.5041]	[0.2208]	[0.0752]	[0.0355]	[0.1989]
coh99 x rain_shock	-0.826*	-0.545**	0.121*	0.0263	-0.0961
	[0.4732]	[0.2507]	[0.0664]	[0.0378]	[0.2180]
coh00 x rain_shock	-0.527	-0.454*	0.118*	0.00320	0.307
	[0.3765]	[0.2433]	[0.0635]	[0.0438]	[0.2142]
coh01 x rain_shock	-0.494	-0.288	0.142**	0.0772	0.100
	[0.3694]	[0.2118]	[0.0659]	[0.0673]	[0.2418]
Observations	3729	3705	2777	3765	3377
R^2	0.58	0.76	0.08	0.03	0.02
Mean	33.42	38.08	0.384	0.273	1.282
rain_shock= 1 if standardized precipitation anomaly> 1					
coh97 x rain_shock[e]	-0.838	-0.181	.	0.0244	0.0832
	[0.5606]	[0.2299]	.	[0.0580]	[0.2725]
coh98 x rain_shock	0.137	-0.0443	0.0229	-0.00490	-0.0138
	[0.5236]	[0.2706]	[0.0781]	[0.0317]	[0.1619]
coh99 x rain_shock	0.241	0.295	-0.0685	0.00160	-0.109
	[0.4640]	[0.2963]	[0.0808]	[0.0363]	[0.1606]
coh00 x rain_shock	0.436	0.249	-0.0309	-0.00599	0.117
	[0.3211]	[0.2736]	[0.0722]	[0.0315]	[0.1738]
coh01 x rain_shock	0.0869	0.230	-0.0489	-0.0719	0.0667
	[0.3684]	[0.2221]	[0.0747]	[0.0561]	[0.2524]
Observations	3729	3705	2777	3765	3377
R^2	0.57	0.75	0.08	0.03	0.02
Mean	33.42	38.08	0.384	0.273	1.282

Standard errors clustered by gridcell [in brackets]. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[a] Weight and height are measures in pounds and inches respectively and are normalized by age.

[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 of a healthy reference population [World Health Organization 1979].

[c] Anemia is a binary variable = 1 if the child is anemic. Anemia is defined as hemoglobin less than 11 g/dL adjusted for altitude using standard adjustments [Guillermo Jose Ruiz-Arguelles and Antonio Llorente-Peters, 1981]. See also Gertler, 2004.

[d] Number of days in the previous 4 weeks that the child was reported sick by the mother.

[e] *coh97 x rain_shock* indicates the interaction between the variable *coh97* (=1 if the child was born in 1997) and the variable *rain_shock* (=1 if a rainfall shock occurred in 1999).

Table A.6: Sensitivity tests: analysis presented in table 4 are reproduced using rainfall variables corresponding to two different cutoff points (standardized precipitation anomalies higher than 1 and 0.5 standard deviations respectively). As in table 4, this table presents estimates the effect of the 1999 September-October rainfall shock on cognitive development indicators measured in 2003 for children born between 1997 and 2001: Peabody Test Scores (i.e. language abilities), and Woodcokc-Muñoz test Scores (i.e. long-term memory, short term memory, and visual-spatial thinking. Test scores are measured in logs.

	Peabody Test[a]	**Woodcock-Muñoz Test**[b]		
	language	long term memory	short term memory	visual-spatial thinking
	(1)	(2)	(3)	(4)
rain_shock= 1 if standardized precipitation anomaly > 0.5				
coh97 x rain_shock[c]	-0.267***	-0.254***	-0.0113	-0.136***
	[0.0975]	[0.0872]	[0.0245]	[0.0403]
coh98 x rain_shock	-0.176**	-0.216***	-0.00883	-0.117***
	[0.0833]	[0.0611]	[0.0255]	[0.0311]
coh99 x rain_shock	-0.0776	-0.160**	-0.0580	-0.138***
	[0.0822]	[0.0692]	[0.0400]	[0.0481]
coh00 x rain_shock	0.000209	-0.150**	-0.0132	-0.149***
	[0.0728]	[0.0619]	[0.0391]	[0.0517]
coh01 x rain_shock	.	-0.0547	-0.0825	0.135
	.	[0.0499]	[0.0552]	[0.0974]
Observations	2835	3522	3385	2967
R^2	0.33	0.32	0.48	0.38
rain_shock= 1 if standardized precipitation anomaly > 1				
coh97 x rain_shock[c]	-0.0872	-0.0997	0.0193	-0.0863*
	[0.1018]	[0.1001]	[0.0242]	[0.0453]
coh98 x rain_shock	-0.0910	-0.137*	-0.0203	-0.0589
	[0.0680]	[0.0742]	[0.0273]	[0.0417]
coh99 x rain_shock	0.0225	0.00479	0.0263	-0.00585
	[0.0762]	[0.0654]	[0.0421]	[0.0587]
coh00 x rain_shock	0.00675	-0.0499	0.0386	-0.0781
	[0.0646]	[0.0660]	[0.0343]	[0.0575]
coh01 x rain_shock	-0.221	0.0179	-0.0430	0.0866
	[0.7175]	[0.0570]	[0.0543]	[0.0758]
Observations	2835	3522	3385	2967
R^2	0.33	0.31	0.48	0.38

Standard errors clustered by gridcell [in brackets]. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[a] Peabody Test measures verbal abilities, scores are standardized by age. Peabody test scores are a reliable predictor of achievements in primary school.

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

[c] *coh97 x rain_shock* indicates the interaction between the variable *coh97* (=1 if the child was born in 1997) and the variable *rain_shock* (=1 if a rainfall shock occurred in 1999).

Table A.7: Sensitivity tests: analysis presented in table 5 are reproduced using rainfall variables corresponding to two different cutoff points (standardized precipitation anomalies higher than 1 and 0.5 standard deviations respectively). As in table 5, this table shows the effect of the 1999 September-October rainfall shock on gross motor skills measured in 2003 for children born between 1997 and 2001: ability to keep their balance on one foot (measured in seconds), ability to work forward and backward. These gross motor skills are central to the successful performance of school tasks.

	balance on one foot (seconds)[a]	ability to walk backward[b]	ability to walk straight[b]
	(1)	(2)	(3)
rain_shock= 1 if standardized precipitation anomaly> 0.5			
coh97 x rain_shock[c]	-0.471	0.0392**	0.00646
	[0.3474]	[0.0186]	[0.0130]
coh98 x rain_shock	0.143	0.0210	0.0234*
	[0.2689]	[0.0136]	[0.0135]
coh99 x rain_shock	-0.356	0.0160	-0.0377**
	[0.3647]	[0.0165]	[0.0175]
coh00 x rain_shock	-0.180	-0.0186	-0.0112
	[0.3692]	[0.0333]	[0.0414]
coh01 x rain_shock	0.162	-0.0664	0.0653
	[0.4701]	[0.0471]	[0.0537]
Observations	3563	3693	3663
R^2	0.33	0.16	0.24
Mean	8.286	0.891	0.843
rain_shock= 1 if standardized precipitation anomaly> 1			
coh97 x rain_shock[c]	-0.242	0.0294**	0.00733
	[0.3547]	[0.0146]	[0.0114]
coh98 x rain_shock	0.0606	0.0107	0.0211*
	[0.2620]	[0.0122]	[0.0107]
coh99 x rain_shock	0.304	0.0314*	-0.0103
	[0.3564]	[0.0164]	[0.0172]
coh00 x rain_shock	0.192	-0.0210	-0.0309
	[0.3696]	[0.0309]	[0.0379]
coh01 x rain_shock	0.390	-0.00394	-0.0245
	[0.3915]	[0.0569]	[0.0415]
Observations	3563	3693	3663
R^2	0.33	0.16	0.24
Mean	8.286	0.891	0.843

Controlling for household and individual characteristics.

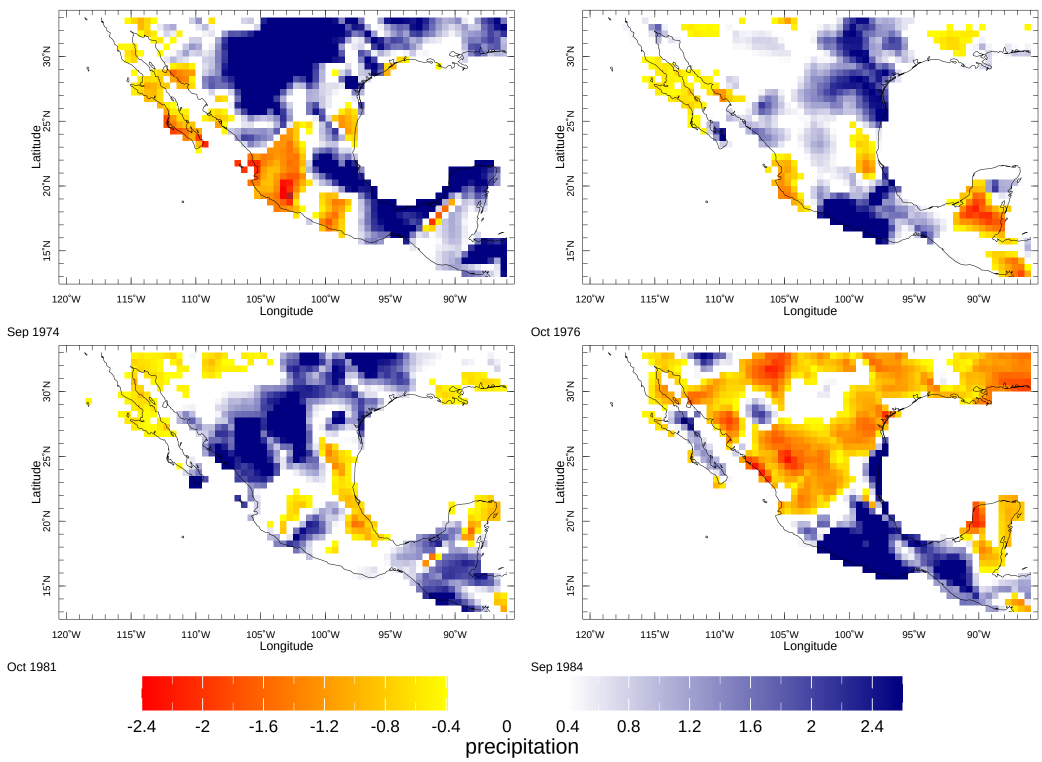
Standard errors clustered by gridcell [in brackets]. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[a] The child's ability keep her/his balance on one foot is measured in seconds.

[b] The binary variables = 1 if the child was able to successfully complete the task.

[c] *coh97 x rain_shock* indicates the interaction between the variable *coh97* (=1 if the child was born in 1997) and the variable *rain_shock* (=1 if a rainfall shock occurred in 1999).

Figure A.1: ENSO historical. Precipitation Standardized Anomalies (UEA CRU Ts2p1)



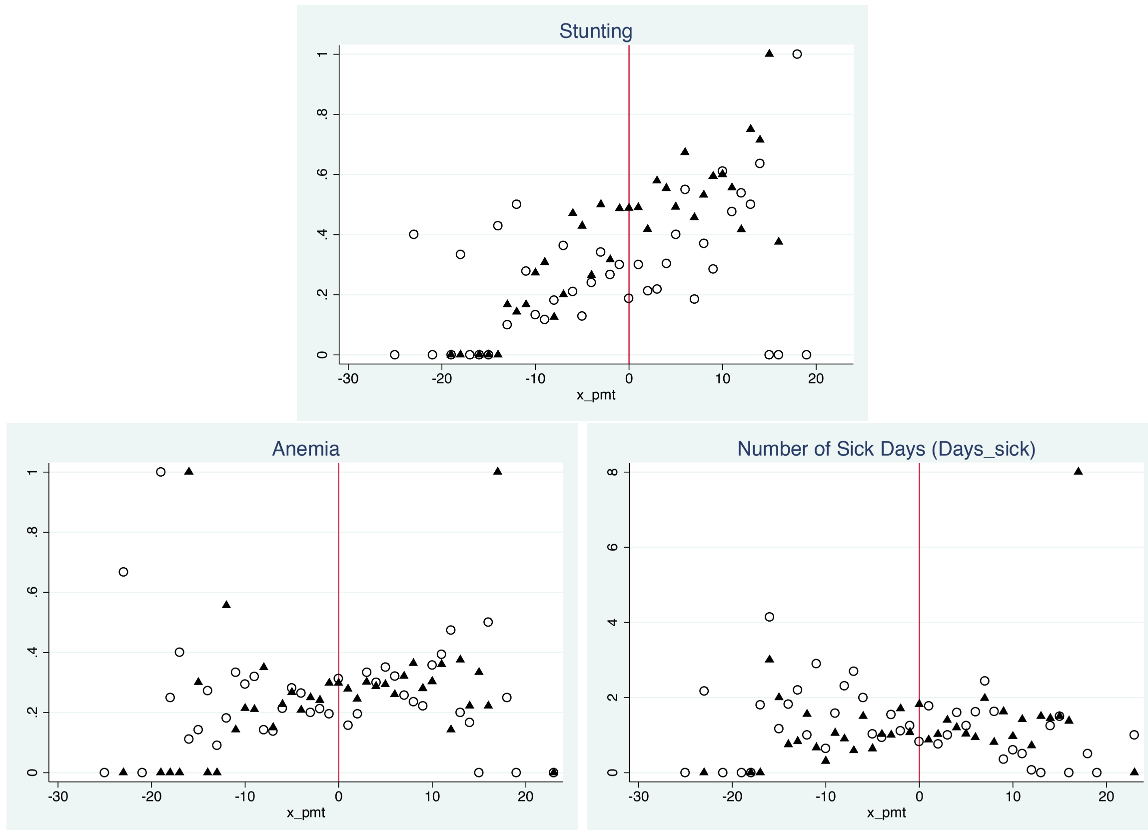


Figure A.2: RD analysis: Anthropometric Outcomes

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 conditional means of the individual outcomes. ▲is the conditional mean for individuals from villages affected by a rain shock. ○is the conditional mean for individuals from villages not affected by a rain shock.

Figure A.3: RD analysis: Cognitive Outcomes

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 conditional means of the individual outcomes. ▲is the conditional mean for individuals from villages affected by a rain shock. ○is the conditional mean for individuals from villages not affected by a rain shock.