Mitigating the Persistent Effects of Early-Life Shocks: Evidence from Safety Net Programs in Colombia *

Valentina Duque[†] Maria Rosales-Rueda[‡] Fabio Sanchez[§]

This Draft: January 24, 2017

Abstract

Although the early-origins literature in economics and other disciplines suggests that early-life shocks have long-term consequences, it does not investigate whether later human capital investments have the potential to mitigate such consequences. This study examines how early-life conditions interact with subsequent human capital investments to influence future educational outcomes. To provide causal evidence, we exploit two sources of exogenous variation: i) variation in early-life environments resulting from a child's exposure to extreme rainfall and drought shocks in early-life; and ii), variation in subsequent investments resulting from the availability of conditional cash transfers (CCT) that promote investments in children's health and education. Using Colombian administrative data, we combine a natural experiment with a regression discontinuity design using the CCT assignment rule. Results show that although the CCT has an overall positive impact on children's educational outcomes that is robust to accounting for exposure to negative shocks early in life, there is limited evidence that the CCT has a differential effect on children exposed to early shocks. However, the main effect of the CCT is large enough to offset the negative impact of the weather shock. These findings have important policy implications as they provide evidence of the role of social policies in closing gaps generated by early-life trauma.

Keywords: Early-life influences, Human development, Social programs
JEL Codes: J13, O15, I38

*We thank Ach Adhvaryu, Anna Aizer, Richard Akresh, Orley Ashenfelter, Javier Baez, Raquel Bernal, Marianne Bitler, Hoyt Bleakley, John Bound, Adriana Camacho, Janet Currie, Hank Farber, Brian Jacob, Ilyana Kuziemko, Mike Mueller-Smith, Chris Neilson, Pablo Ottonello, Lesley Turner, Miguel Urquiola, Atheendar Venkataramani, Tom Vogl, Melanie Wasserman, Dean Yang and participants at the ERC and CHW seminars at Princeton University, H2D2 and CIERS seminars at University of Michigan, PopPov 2016, APPAM International 2016, University of Los Andes (Colombia), PAA 2016, and the World Bank (Regional Study on Shocks and Poverty) and CAF (Capital Humano y Habilidades para la Vida y el Trabajo) seminars. We also thank Andres Cordoba, Isabel Hincapie, Isabela Munevar, Tatiana Velasco, and Xiomara Pulido for excellent research assistance. Funding for this work was generously provided by CAF. All errors are our own.

[†] vduque@umich.edu, University of Michigan
[‡] mfrosale@uci.edu, University of California, Irvine and Princeton University
[§] fasanche@uniandes.edu, University of Los Andes

1 Introduction

A growing body of research has shown that conditions experienced by age 5 influence individual's long-term outcomes, including education, income, and health (Almond and Currie, 2011; Barker, 1992; Cunha and Heckman, 2007). However, much less is known about whether the negative impacts of early-life shocks can be undone: Could the actions of parents or governments help mitigate those effects? This question is especially important in developing countries where more than 200 million children are at risk of not reaching their full potential due to poverty and other challenges (Currie and Vogl, 2013; Grantham-McGregor et al., 2007).

A priori, whether early-life shocks and investments can interact remains an open question. Theoretical models on human capital formation predict the existence of dynamic complementarities: investments at one stage of development may make subsequent investments more productive (Cunha and Heckman, 2007). However, some studies have actually found that returns can be more pronounced among vulnerable groups (Bitler et al., 2014; Havnes and Mogstad, 2011; Wherry and Meyer, 2015).

We contribute to the literature by investigating how early-life conditions interact with subsequent investments to influence long-term educational outcomes using Colombian administrative data. The lack of evidence of the interactions between initial endowments and subsequent investments can be partly explained by its endogenous relationship: child conditions and parental and government responses can be jointly determined with future outcomes by unobserved factors (e.g., preferences). As discussed in Almond and Mazumder (2013), to arguably estimate a causal link, one should identify a cohort exposed to exogenous variation in both early-life environments and in subsequent human capital investments. We address these challenges by exploiting two sources of arguably exogenous variation: i) variation in early-life conditions resulting from a child's exposure to weather shocks in the place of a child's birth and during his/her first years of life; and ii), variation in later life human capital investments resulting from the introduction of the conditional cash transfers program

(CCT) in Colombia. Our results show that, although we find a negative and a positive impact from exposure to weather shocks and the CCT, respectively, on child's educational outcomes, there is little evidence of an interaction effect.

In particular, our first source of variation of early-life conditions comes from the occurrence of extreme weather events in Colombia during the 1990s: El Niño droughts of 1991-1992 and 1997-1998 and La Niña floods during 1998-2000. These shocks were particularly and unexpectedly intense and long in duration, and had tremendous impacts on the socio-economic conditions of the local communities. We exploit geographic and temporal variation in rainfall exposure at the municipality-month-year levels, in the place of a child's birth and during his/her early-stages as a natural experiment. We focus on these weather events for several reasons: i) they were exogenous; ii) they provide very large variation in early-life environments; and iii), they occurred right before the CCT program was launched and so they serve our identification strategy in terms of the timing of events affecting the same cohort.

The second source of variation that helps measure investments in children's health and education comes from the eligibility mechanism into Colombia's CCT program, *Familias en Accion (FeA)*. FeA was launched in 2001 and targeted to the poorest households in the country based on a poverty index score (Sisben). We exploit the assignment rule to the program using a regression discontinuity design (RDD) that allows us to compare families on both sides of the cutoff that are similar in all their observable characteristics (including the likelihood of experiencing early-life shocks) except for their eligibility to the program. We focus on CCTs because these programs have become very popular in developing countries and they have been successful in promoting parental investments in children's health and education.

We then combine these two sources of variation using a natural experiment with a regression discontinuity framework. This strategy allows us to test the hypothesis of whether children who were born or lived through their early years in areas more affected by the rainfall-drought events of the 1990s, and who later received the CCT benefit, were able to catch up with children who received the benefit but who did not experience the shock. In other words, we ask if the CCT helped mitigate to some extent the El Niño and La Niña negative effects.

We leverage several sources of large-scale administrative data in Colombia. First, we use the "Census of the poor" or Sisben I, which includes basic demographic and socioeconomic characteristics, as well as the poverty index score that targets families into the CCT, for the poorest 25 million individuals in Colombia.[1] Using individual-level identifiers, we merged the Sisben with the master dataset of students in the public schools in Colombia obtained from the Ministry of Education and with data on all students taking the end-of-high school national exam, Icfes. Lastly, we merged these data with the information system on Familias en Accion beneficiaries. Rainfall information was obtained from the Colombian Institute of Meteorology and Climate Conditions (IDEAM), which is merged at the municipality-month-year levels. Given our research design, our sample includes all cohorts of children born in the 1990s in Colombia and our outcomes of interest are: i) age-appropriate grade completion (age-on track), ii) high school graduation, and iii) Icfes test score which is a national exam that all high school graduates take regardless of whether they intend to apply to college (i.e a high school exit exam).

This paper shows three set of findings. First, using the natural experiment, we show that exposure to weather shocks from in-utero up to age 3 undermines future human capital formation. In particular, our findings reveal that experiencing extreme weather events in early-life reduces age-on-track and high school graduation by 2.7% and 2.1% of the mean respectively, and Icfes scores by 0.085 standard deviations (SD). Results do not seem to be driven by potential sources of selection bias such as migration, fertility, and child mortality.

Second, using the RDD that exploits the assignment rule to Familias en Accion based on the Sisben score, we show that receiving the CCT increases age-on-track, HS graduation,

[1]Colombia's population is 48 million.

and Icfes by: 3.9%, 17.1%, and 0.14 SD, respectively. Also, we show that these effects of the program on long-term outcomes are not likely driven by selective fertility or migration responses.

Lastly, we investigate the scope of mitigation. We explore the marginal effect of receiving the cash transfer on children affected by weather shocks, net of the average effect of Familias en Accion. Results show limited evidence that the CCT has differential effects on children exposed to the weather shocks since the estimates of the interaction are imprecise (except for appropriate grade completion). We find, however, that weather-affected children who receive Familias en Accion are able to overcome the negative effect of the weather shock since the CCT has an overall positive impact that is robust to accounting for exposure to negative shocks early in life. In addition, weather-affected children partially catch up with unaffected ones. Hence, the cash transfer does seem to partially close the gaps due to early-life inequality.

Our study complements three bodies of research. First, we contribute to an emerging literature exploring the interaction between two exogenous shocks on individual outcomes where the evidence is so far mixed. For instance, while Aguilar and Vicarelli (2012) found that Progresa, Mexico's CCT program was unable to mitigate the effects of extreme weather shocks (i.e., El Nino) on children's health and cognitive development, Adhvaryu et al. (2015), using similar data for Mexico, found that Progresa actually helped remediate the effect of extreme rainfall on educational attainment by almost 80%. Gunnsteinsson et al. (2014) for Bangladesh, also found that maternal and newborn vitamin A-supplementation helped reduce the negative effects of a tornado. For the case of Romania, Malamud et al. (2016) found that although children who experienced better early-life environments (due to access to abortion) and children who had access to better schools each had positive impacts on test scores, there was little evidence of a significant interaction between these two shocks. Lastly, Rossin-Slater and Wüst (2015) for Denmark, examined whether children who received two early-life investments (i.e., were enrolled in a home visiting program and then attended a child-care center) had larger returns compared to children who only received one of the investments. Results show that returns were actually similar across both cases, providing some evidence of substitution impacts across investments. A related body of research has also found differences in the returns of positive shocks in early-life across subgroups. For instance, Bhalotra and Venkataramani (2015) found that the long-term positive impacts of the introduction of antibiotics in the US in 1937 varied across Black men who were exposed to different levels of institutional segregation in their state of birth. Aizer and Cunha (2012) also found that, relative to older siblings, children who participated in Head Start had higher test scores and that these effects were greatest for children with the highest initial human capital endowments.

Second, our paper is also related to previous work discussing the disruptive effects of weather events on child development and long-run outcomes (Aguilar and Vicarelli, 2012; Baez et al., 2010; Currie and Rossin-Slater, 2013; Maccini and Yang, 2009; Pathania, 2007; Rocha and Soares, 2015; Rosales-Rueda, 2016; Shah and Steinberg, 2016). We contribute to this research by being one of the first papers to document the long-term impacts of weather shocks on individual outcomes using school administrative data. To our knowledge, most evidence has focused on examining short and medium-term impacts from early-life exposures on outcomes such as child's height, cognitive skills, and school enrollment (Aguilar and Vicarelli, 2012; Baez and Santos, 2008; Rosales-Rueda, 2016), and while a few have documented effects of rainfall on educational attainment (Maccini and Yang, 2009), little is known about effects on long-term achievement test scores.

The third literature that this paper refers to is the extensive research on the effects of CCTs on human capital. The World Bank in a recent review on the effects of CCTs concluded that,"CCTs have been successful in reducing poverty and encouraging parents to invest in the health and education of their children" (Fiszbein and Schady, 2009, pg. xi). Outcomes such as household's consumption, school enrollment, nutrition, child vaccinations, health care visits, and child's cognitive test scores have been positively affected by the cash benefit

(Attanasio et al., 2005, 2006, 2005; Attanasio and Mesnard, 2006; Baez and Camacho, 2011; Macours et al., 2012; Paxson and Schady, 2007, and many others). Our study contributes to this growing body of research by showing novel evidence on the positive effects of CCTs on age-appropriate grade completion and end of high-school achievement test scores.

This paper is structured as follows. The next section describes the El Niño and La Niña weather shocks during the 1990s in Colombia as well as the conditional cash transfer program Familias en Accion. Section 3 presents the data sources, Section 4 discusses the empirical methods, and Section 5 presents our main results. Section 6 explores some selection concerns and robustness checks. Lastly, we provide some conclusions in Section 7.

2 Background

2.1 Weather shocks

Weather shocks are perhaps one the most adverse conditions faced by households in developing countries (Fay et al., 2015). Using data over the last half-century, Dell et al. (2012) showed that increases in temperature in poor countries were associated with substantial declines in economic growth, agricultural and industrial output, and induced political instability, while no effect was observed in developed nations. Weather shocks experienced early in life can be particularly harmful as research has documented significant declines on child's health, education, nutrition, and cognitive development (Currie and Vogl, 2013; Rosales-Rueda, 2016).

Recent trends in global climate change suggest that weather events like droughts and floods can become more frequent in the near future and that their intensity may be less predictable, thereby imposing bigger challenges for those living in vulnerable areas (Kovats et al., 2003). For instance, from 1987 to 1998, the average number of annual weather disasters was 195, while from 2000 to 2006, this number increased to 365 (Garlati, 2013). Gitay et al. (2013) estimated that between 1980 and 2012, damages and losses due to weather disasters amounted to $2.6 trillion US dollars. Children bear a sizable proportion of the consequences from weather disasters. Compared with adults, they are more vulnerable to the direct and indirect consequences of severe weather events but often are left out of discussions. According to the World Health Organization, children suffer around 80% of the health damages from climate change. Also, Save the Children estimates that the number of children affected by natural disasters will increase from 66.5 million per year in late 1990's to 175 million per year in the next decade (Baker and Kyazze, 2008; Currie and Deschnes, 2016).

In this paper, we focus on two recent weather shocks that affected Colombia and the Pacific South America during the 1990s: El Niño 1991-1992 and 1997 and La Niña 1998-2000. We describe each of these episodes below.

2.1.1 El Niño 1991-1992 and 1997 and La Niña 1998-2000

El Niño and La Niña are complex weather patterns resulting from variations in ocean temperatures in the Equatorial Pacific.[2] El Niño and La Niña are opposite phases of what is known as the El Niño-Southern Oscillation (ENSO) cycle: while El Niño is characterized by unusually warm ocean temperatures, La Niña is associated with unusually cold ones. El Niño produces droughts in the western coast of Central America, Mexico, and the northern South America, from Colombia to northern Brazil, whereas it causes floods and landslides in Peru, Ecuador, Bolivia, and Chile. The opposite pattern is observed during la Niña, which for the case of Colombia, it manifests in the form of intense floods (Hoyos et al., 2013). Moreover, although el Niño and La Niña are recurrent events, their cycles are irregular, making their timing and intensity hard to predict. For instance, the ENSO can vary in length from two to seven years (Kovats et al., 2003).

Compared to previous events in the twentieth century, El Niño droughts of 1991-1992 and 1997-1998 and La Niña floods of 1998-2000 were particularly and unexpectedly long in duration and strong in magnitude. The 1991-1992 and 1997 El Niño events lasted 16 and

[2]More information on El Niño and La Niña shocks can found here:
http://oceanservice.noaa.gov/facts/ninonina.html.

15 months, respectively (from April 1991 to July 1992 and from March 1997 to May 1998), while the 1998-2000 La Niña event lasted 31 months (from June 1998 to Dec 2000). Figure 2 shows the geographic variation in exposure to these three events, which is different for each shock.

The 1991-92 drought was so strong and unexpected that it led to extremely low levels of water accumulation in the hydroelectric dams, resulting in a dramatic decline in power generation and in a 12-month period of daily electricity rationing across the country. Also, these droughts translated into deficits in water supply. The agricultural sector productivity was severely affected: in 1992, cotton, sorghum, and potatoes crops experienced productivity losses of 70%, 35% and 20%, respectively (Carvajal et al., 1999). In 1997-1998, the atypically intense El Niño droughts also led to numerous forest fires that affected around 90% of the country (IDEAM, 2002). CAF (1998) estimated that the economic sectors more severely affected were electricity and water supply, agriculture, and health care services. According to Campos et al. (2012), around 20% of Colombian municipalities were severely affected by shortages and low quality of water supply.

During 1998, a rapid transition between El Niño and La Niña occurred and drastic weather fluctuations affected different regions of the country, switching from strong droughts to devastating floods. Between the end of 1998 and throughout the year 2000, there were severe flooding and landslides associated with La Niña, which affected 769 municipalities (of the 1,100 in Colombia) in 22 states (of the 33). The economic sectors more affected during these years were agriculture, infrastructure, and health care services. Additionally, another relevant consequence of the 1998-2000 La Niña was the increase in the incidence of infectious diseases like dengue, colera and malaria (CAF, 1998).

2.2 Conditional cash transfer programs (CCTs)

Since the 1990s, many developing countries have implemented CCTs to reduce poverty and encourage parental investments in their children's health and education, and the evidence shows important improvements in these respects (Fiszbein and Schady, 2009). Familias en Accion (FeA) is Colombia's CCT program, which was launched in 2001 inspired by the Mexican CCT program Oportunidades.

FeA expanded rapidly in Colombia until 2010, when the program reached national coverage. The implementation of the program took place in three stages. In the first phase of FeA (the phase of interest in this paper), the program became available in 627 municipalities (out of the 1,098), which were deemed eligible to qualify for the program (Figure 3). The targeted municipalities could not be department capitals, had to have less than 100,000 inhabitants, a certain capacity of health and education infrastructure, up-to-date information systems of welfare recipients, and at least one bank (for the cash benefit to be transfered to program beneficiaries).

The program started with approximately 600,000 beneficiary households between 2001 and 2004.[3] Since 2005, the program was expanded to include other vulnerable populations such as the forcefully displaced families[4], as well as poor households in departmental capitals and households in municipalities that were now able to offer the required health, education, and bank services (i.e., developed their own infrastructure or where close in distance to towns that had the required public services).

As of 2007, the program expanded to municipalities with more than 100,000 inhabitants to include other deprived urban areas. Today, FeA operates nationwide, serves around three million families, and constitutes the largest social investment in Colombia (Attanasio et al., 2012, 2010; Baez and Camacho, 2011; DPS-DNP, 2013). Research examining the effects of Familias en Accion has found positive impacts on household's consumption and on children's health and educational outcomes (Attanasio et al., 2005, 2010, 2005; Attanasio and Mesnard, 2006; Baez and Camacho, 2011) and the magnitudes of these effects are within the range of

[3]Colombia's population is 48 million.

[4]Forced displacement has been one of the most dramatic consequences of the armed conflict in Colombia. The total displaced population in the country reached over 3.5 million since 1997, 8% of the total population (United Nations High Commissioner for Refugees, 2010). Displaced groups tend to have very low socioeconomic indicators, including educational attainment and health status.

those found in the literature of CCTs (Fiszbein and Schady, 2009).

FeA provides two types of incentives: 1) health and nutrition transfers for families with children below age 7, conditional on regular medical check-ups; and 2), education transfers for families with children between 7 and 18 years of age, conditional on regular school attendance (minimum required attendance is 80%). The amount of the monthly health grant is $US19 per family with eligible children, while the education subsidy is $US6 and $US12 per child attending primary and secondary respectively.[5]

Eligibility to FeA is based on the Sisben ("Sistema de Identificacion de Beneficiarios"), a poverty index score. The Sisben index, which ranges from 0 (poorest) to 100 (less poor), is calculated using a proxy means test based on a household's characteristics such as consumption of durable goods, head of household's education, and current income. According to their Sisben score, households are divided into 6 levels, of which FeA exclusively targets the poorest one (Sisben level 1), while other social programs such as subsidized health care or retirement pensions, usually target levels 1 and 2.[6] Table 1 shows the Sisben score cutoffs that determine eligibility to the program (note that the thresholds vary for rural and urban regions).

3 Data

3.1 Administrative sources

The richness of the data is one of the major strengths of this study. We merge four sources of administrative data that are: i) the "universe of the poor" or SISBEN I, ii) public schools records (R-166 data), iii) end of high school test scores known as the Icfes national exam records, and iv), the system of beneficiaries of Familias en Accion. Below, we describe

[5]The health subsidy corresponds to 15% of the minimum monthly wage, while the primary and secondary school grants correspond to 5% and 9% respectively

[6]The fact that FeA only targets level 1 while other programs target levels 1 and 2, actually represents a strength of our identification strategy as there is little change in eligibility to other social programs that could be confounded with FeA.

each of these sources.

3.1.1 The "Universe of the Poor": the SISBEN

We use the core data of Sisben I that was collected from 1993 to 2003.[7] This dataset includes rich demographic and socioeconomic information on over 25 million individuals –the poorest in the country. The Sisben represents the main dataset in this study, as it allows us to identify both the eligible and non-eligible households for Familias en Accion. To link individuals from other datasets to the Sisben, we use their individual identifiers such as full names (first and middle names and fathers' and mothers' maiden names), birth dates (day, month, year), and national ID numbers (type of document and number), which were all available for each of the different sources. Hence, all the information is centralized around the Sisben.

3.1.2 The Universe of Students in Colombia's Public Schools: the R-166

The second source is the core database of the Ministry of Education. This dataset began with the 'Resolution 166' of 2004 that mandated the Ministry to collect and report detailed information on the school progression of all students enrolled in the public school system in Colombia, starting in the first year a child entered the school system (e.g., first grade) up to high school graduation (or drop-out).[8] In this paper, we use the universe of students in R-166 from 2005 to 2015. The dataset provides key educational outcomes that capture a child's performance in school for a sample of approximately 85 million student-year observations. A unique advantage of using the R-166, is that it includes the exact municipality of birth for each student, which is not available in any other administrative dataset.

[7] The subsequent waves of Sisben, II and III, were collected in 2005 and in 2010, respectively.

[8] More information on this resolution is found here: http://www.mineducacion.gov.co/1759/w3-article-163147.html.

3.1.3 The End-of-High School Exam: the Icfes

The Icfes is the national high school exit exam administered by the *Instituto Colombiano para el Fomento de la Educacion Superior*. It is taken by high school seniors regardless of whether they intend to apply to college and it includes separate tests on math, Spanish, social studies, sciences, and an elective subject. We use information from all students who took this exam from 2000 to 2014 (approximately one million observations).

3.1.4 The System of Beneficiaries of Familias en Accion

The dataset of Familias en Accion beneficiaries is a longitudinal census of the universe of program participants. It includes detailed information such as demographic and socioeconomic characteristics, the amount transferred ($) to a family, the type of benefit (education or health) that a child receives, a family's exposure to the program (measured in months), etc. We use data from the first phase of FeA, which covers the period from 2001 to 2004 and which includes records of 2.8 million individuals living in 627 municipalities (Figure 3).

3.2 Rainfall data

The data on rainfall comes from the Colombian Institute of Meteorology and Climate Conditions (IDEAM), which registers rainfall levels in each of the 1,100 municipalities in Colombia since 1980.[9] To identify rainfall shocks, we focus on el Niño (droughts) and la Niña (floods) events during the 1990s. For ease of interpretation, we define rainfall shocks as whether the standardized precipitation (in mm) in a particular month and municipality exceeded the historical standardized mean precipitation in that municipality and in that month by plus/minus one standard deviation or more. In other words, we consider both flood and droughts as being a similar shock. This categorization has been widely used in previous studies on weather conditions and climate change (Guerreiro et al., 2008; Seiler et al., 2002).

[9]To determine a municipality rainfall level, the authors construct a weighted average of the rainfall levels from the closest IDEAM stations to the municipalities, which are weighted by the distance from each station to the municipality node.

The rainfall dataset is merged to the administrative datasets at the municipality-month-year levels.

3.3 Sisben Manipulation and Sample of Interest

Sisben Manipulation. A key identification assumption of the regression discontinuity design is that individuals have imprecise control over their Sisben score; in other words, that individuals are randomly assigned around the cutoff.[10] Camacho and Conover (2011) documented that manipulation of Sisben was a relatively common practice among politicians in Colombia, who exchanged Sisben-related benefits for votes in the local elections. In particular, the authors found that this practice occurred around the cutoff between Sisben levels 2 and 3, where the bundle of social benefits becomes more generous.

Although the relevant cutoff in this study is that between Sisben levels 1 and 2 (that affect eligibility to FeA), we carefully check if the Sisben score, the running variable, is being manipulated in the assignment of families around the threshold. Figure 4 shows the distribution of Sisben by urban and rural areas. A visual inspection suggests some evidence of manipulation between levels 1 and 2 in the rural areas (Panel B). In particular, we find a heap on the density of families around the threshold from group 1 to group 2, while this is not observed in urban areas. In addition, we perform a version of the McCrary test for manipulation when the running variable is discrete (Frandsen, 2016). We fail to reject the null hypothesis of no manipulation for urban families, while we reject it for rural families. Based on this finding, we perform all our analyses focusing on households living in urban areas.

[10] Two other important identification assumptions are: i) monotonicity (i.e., the Sisben score crossing the cutoff cannot simultaneously cause some families to take up and others to reject the cash transfer.) ii) Excludability (the Sisben score crossing the cutoff cannot impact the outcomes except through impacting receipt of FeA). These assumptions imply that we are estimating a Local Average Treatment Effects for the compliers (Lee and Lemieux, 2010).

Sample of Interest. We restrict our data to children who were born between 1988 and 2000 in Colombia, who have information on their municipality of birth, whose families live in urban areas and are either in Sisben level 1 (eligible to FeA) or in Sisben level 2 (non-eligible) We focus on these cohorts because they were eligible for FeA phase I at an early-enough stage (i.e., previous cohorts were too old to receive the transfer) and because their early-years coincided with the occurrence of El Niño and La Niña events of 1991-92 (drought), 1997-98 (drought), and 1998-2000 (floods). Subsequently after the last weather shock of 2000, children and their families were exposed to the introduction of the cash transfer program in 2001.

3.4 Period of exposure to early-life shocks

Following the literature in developmental psychology, epidemiology, and more recently in economics on sensitive periods for skill formation (Gluckman and Hanson, 2005; Heckman, 2008; Knudsen et al., 2006; Thompson and Nelson, 2001), we focus on specific periods of a child's early life, which we defined as in utero (9 months before birth) and early childhood years (ages 0-3). We use both the date of birth and the municipality of birth to identify these stages. For example, in-utero exposure is determined by counting backwards 9-months since a child's month of birth in the municipality of birth. Exposure in early childhood would cover the first 3 years of life (starting in the month after birth +36 months). Exposure to rainfall shocks captures whether a shock occurred in a given month during each of these developmental stages in the municipality of birth.

3.5 Outcome Variables

The following list describes the outcomes of interest:

1. **Age on track:** a dummy variable, takes the value of one when a child has completed the appropriate years of schooling for his/her age and zero otherwise.[11] Seventy-five

[11] By law, all children must start the school cycle prior to age 8.

percent of students are on track for their age (Table 2).

2. **High school graduation:** a dummy variable, takes the value of one when an individual has finished high school and zero otherwise. Sixty-three percent of students graduate from high school (Table 2).

3. **Icfes score:** end of high school test score that averages over all subjects. This is a high stake exam as it significantly influences admissions to college. It varies between 0 and 100, with a mean of 44.45 and a standard deviation of 5.68 (Table 2).

The sample of interest varies by outcome measure. In the case of Icfes test scores, it includes more than 100,000 students between 16 and 24 years of age while in the case of school progression, the sample includes around 300,000 individuals.

3.6 Descriptive Statistics

Table 2 shows summary statistics on all children born between 1988 and 2000, whose families are either eligible (Sisben level 1) and non-eligible (Sisben level 2) to receive Familias en Accion. Overall, we find that children in Sisben level 1 and 2 come from disadvantaged households. For instance, only 30% come from families where the parents are married, and 85% live in households where the head has primary education or less. Households tend to have on average 6 to 7 members. In addition, column 2 shows that families around the cutoff are fairly similar to the full sample of eligible and non-eligible families.

Regarding exposure to the 1990's El Niño and La Niña events, around 87% of CCT eligible and non-eligible children experienced at least one month of extreme weather shocks from conception up to age 3. On average, they were exposed to around 6.5 months of shocks during early-life (with a standard deviation of 4.79 months).

4 Methods

We conduct our empirical analysis in three steps. First, we exploit the geographic and cohort variation in exposure to early-life weather shocks using a natural experiment approach, which allows us to estimate the impact of early disadvantage. Second, we use a regression discontinuity design to estimate the effects of human capital investments. Third, we combine these two sources of variation to estimate the interactions between early-life shocks and subsequent human capital investments.

4.1 Effects of Early-life Shocks on Human Capital

The first step is to estimate how exposure to early life shocks affected later human capital outcomes for our sample of interest. Using a natural experiment design we estimate the following regression:

$$Y_{ijtm} = \beta_0 + \sum_{k=conception}^{k=age3} \delta_k RainfallShock^k_{jtm} + \beta \mathbf{X_i} + \alpha_{\mathbf{j}} + \alpha_{\mathbf{t}} + \alpha_{\mathbf{m}} + \epsilon_{\mathbf{ijtm}} \tag{1}$$

where Y_{ijtm} is the outcome of child i who is born in municipality j, in year t, and in month m. $RainfallShock_{ijtm}$ represents the number of months of exposure to rainfall shocks during el Niño events of 91-92 and 97-98 and la Niña event of 98-00, experienced during the period from conception and up to age 3. Thus, δ_k captures the marginal effect per one month of exposure in each developmental stage of interest. $\mathbf{X}$ is a matrix that includes socio-demographic characteristics of a child and family such as gender, age, mother's age, education, and marital structure, household size, access to water/sewage, and year of Sisben interview.[12] The terms $\alpha_j, \alpha_t, \alpha_m$ denote municipality, year, and month of child's birth fixed effects that help capture time invariant municipality-level characteristics and shocks that are common to all children born in a given year and month. Lastly, ϵ represents the random error term. To address

[12]Information on race/ethnicity is unavailable in the Sisben data.

potential spatial and time correlation, we cluster standard errors at the state level.[13]

The main identifying assumption required to consistently estimate the effects of rainfall shocks on children's outcomes is the independence between the error term and the shock, after controlling for municipalities and cohort fixed effects, and individual characteristics. We provide some evidence on this by examining the presence of sorting of families into rainfall shocks. Table 3 shows the association between family socio-demographic characteristics and exposure to negative shocks across different childhood periods. Results show little evidence that families of certain characteristics may be more likely to experience the events of El Niño and La Niña, providing support for our identification strategy.

4.2 Effects of Investments on Human Capital

Second, we explore whether participating in FeA affected children's long-term human capital. Since participation in FeA is endogenous, we exploit the fact that eligibility into the program is determined by a household's poverty score.

Figure 5 shows program take-up by Sisben score.[14] We find that: (i) the jump in the probability of participating in the program is of 30 percentage points around the cutoff; (ii) among those who are eligible, between 52% and 65% participate in FeA; and (iii) among those who are not eligible to receive FeA, between 20% and 3% actually receive the cash transfer. Given this imperfect compliance, we use a fuzzy RDD (instead of a sharp design) that exploits the Sisben assignment rule as an instrument for FeA participation.[15] Equation 2 describes the first stage:

$$FeA_{ijtm} = \pi_0 + \omega T_i + \lambda g(S_i - c) + \beta \mathbf{X_i} + \alpha_\mathbf{j} + \alpha_\mathbf{t} + \alpha_\mathbf{m} + \upsilon_\mathbf{ijtm} \quad (2)$$

[13]Our results are robust to the inclusion of state-specific linear and quadratic time trends, which help control, for instance, for state level differences in economic development or investments in public goods.

[14]The cutoff Sisben score for group 1 has been normalized to 0.

[15]Previous studies examining the effects of FeA have also used the Sisben score as an instrument for program participation (Baez and Camacho, 2011).

where FeA_{ijtm} represents FeA take-up: an indicator equals to one if the family participate in the program. T denotes if a child/family i is eligible to participate based on whether their Sisben score S is below the relevant cutoff point c ($T_i = 1$ if $S_i < c$ and $T_i = 0$, otherwise). The function $g(.)$ is a parametric but flexible function of a family's Sisben score relative to the cutoff. Following Lee and Lemieux (2010), we allow this function to be different at both sides of the cutoff. To determine the optimal bandwidth, we employ the bandwidth selector procedure proposed by Imbens and Kalyanaraman (2012).

Lastly, equation 3 describes the second stage regression:

$$Y_{ijtm} = \beta_0 + \gamma \widehat{FeA}_{ijtm} + \varphi f(S_i - c) + \beta \mathbf{X_i} + \alpha_\mathbf{j} + \alpha_\mathbf{t} + \alpha_\mathbf{m} + \varepsilon_\mathbf{ijtm} \tag{3}$$

where γ is the coefficient of interest that captures the causal effect of participation in FeA on children's human capital.

We examine whether there are significant differences in observable characteristics across families in the left and right of the cutoff. We estimate reduced-form regressions of each covariate on being eligible to FeA. We find that individuals around the cutoff are similar in observable characteristics. Moreover, Figure 6 provides further support that suggests no discontinuities on individual covariates around the cutoff.

4.3 Interaction between Early-life Shocks and Investments

The final set of analyses investigates whether the negative shocks in early-life can be mitigated by subsequent human capital investments. Equation 4 describes the model that allows us to measure the interaction between FeA and rainfall shocks:

$$\begin{aligned} Y_{ijtm} = &\beta_0 + \sum_{k=conception}^{k=age3} \delta_k RainfallShock^k_{jtm} + \gamma \widehat{FeA}_{ijtm} + \varphi f(S_i - c) \\ &+ \sum_{k=conception}^{k=age3} \tau_k RainfallShock^k_{jtm} * \widehat{FeA}_{ijtm} + \beta \mathbf{X_i} + \alpha_\mathbf{j} + \alpha_\mathbf{t} + \alpha_\mathbf{m} + \xi_\mathbf{ijtm} \end{aligned} \tag{4}$$

δ_k measures the impact of exposure to weather shocks in early stage k for children who did not receive the CCT, while γ measures the effect of the CCT for those who did not suffer early-life climate shocks. The parameter of interest is τ_k that captures the differential effect of FeA for those who suffered negative rainfall shocks in early-life. Comparing the combination of γ and τ_k with δ_k allows us to determine whether children affected by early-life shocks who received the CCT are able to overcome the negative effects of early disadvantage.

We address a potential threat to the validity of this strategy. We examine whether the probability of experiencing negative shocks early in life is differentially distributed across the FeA eligibility cutoff, which could be confounded with the interaction. To address this concern, we check whether the probability of being eligible to FeA (or being on the left of the cutoff) is associated with experiencing negative shocks at the different developmental periods. Table 4 shows that children in families who are eligible to FeA are not necessarily more likely to experience negative rainfall shocks.

5 Results

5.1 The Effects of Early-life Shocks on Human Capital

Table 5 shows the impacts of early life exposure to rainfall shocks on children's outcomes. We present the effects for the full sample (children in Sisben levels 1 and 2, column 1) as well as for the sample in the optimal bandwidth for the RD (column 2). Following the literature on early life shocks and human capital, we also examine the effects of rainfall shocks by trimester of pregnancy and during early childhood (column 3).

Overall, we find that exposure to El Niño and La Niña events have a negative impact on children's education, which confirms that these shocks are an important source of long-term disadvantage. Results show that experiencing these shocks during the third trimester of pregnancy and up to age 3 is particularly harmful: a child exposed to El Niño and La Niña, which on average is a one month of high rainfall/droughts in the third trimester in utero and

5 months in early childhood, experiences a 2.7% fall in the probability of adequate grade progression, a 2.1% decline in the probability of high school completion, and a 0.085 SD fall in the Icfes exam. These estimates are consistent with those in the literature of early-life influences. For instance, Duque (2016) examined the effects of violence in Colombia and found that, children in low educated families (similar to our sample) who were exposed to violence in Colombia during their early years, experienced a 6.3% decline in high school completion and a 0.02 SD decline in the Icfes exam.

5.2 The Effects of Investments on Human Capital

Table 6 shows the effect of receiving FeA on educational outcomes accounting for the endogeneity of participating in the program using the fuzzy RDD approach described in section 4. Overall, we find consistent evidence that receiving the CCT improved children's educational attainment and achievement scores. In particular, participation in the program improves age-appropriate grade progression by 3.9%, increases high school completion by 17.1%, and raises the Icfes score by 0.14 SD. This estimates are consistent with those found in previous research on the effects of CCTs and school outcomes (Fiszbein and Schady, 2009). Interestingly, little research has examined the long-term effects on achievement test scores. To our knowledge, the only evidence comes from Baez and Camacho (2011) who performed a similar strategy to ours (RD framework using the Sisben score as an instrument for FeA take-up) but found no effect (or actually negative impacts) of the program. Two differences between this study and theirs is that we employ a longer period of analysis, from 2000 to 2014, while the authors focus on fewer years of Icfes, and we focus on students in urban sectors while they examine rural and urban areas.

Because the CCT promotes school attendance and improves school completion, we acknowledge that the marginal student who is more likely to complete high school (and thus take the test) due to participation in the program may be different to those who would have finished high school regardless of the CCT. For instance, if those students induced to remain in high school have lower ability, our estimates on the Icfes score are likely to be a lower bound estimate of true impact.

5.3 The Interaction between Early-life Shocks and Investments

Tables 7-9 display the results of the interaction. We first show a model that controls for both the shock and the investment (columns 1 and 2), then we add the interactions between FeA and overall exposure to the shock (column 3), and between FeA and the relevant periods of exposure (columns 4 and 5). To facilitate the interpretation of our results, in the bottom of the Table we present calculations of the effect sizes for three types of children: those who were only exposed to the rainfall shocks, those who were only exposed to the CCT, and those who were exposed to both.

Overall, there is some evidence that FeA has differential effects for children who experienced early-life shocks, although the estimates of the interactions are imprecise (but the magnitudes are non-negligible). For the age-appropriate grade progression outcome, the interaction between rainfall exposure during early childhood (age 0-3) and FeA is positive and statistically significant, suggesting that FeA participation may have an additional positive benefit for children who experienced the shock at younger ages. However, the interactions are no longer significant for longer-term outcomes such as high school completion and end of high school test scores.

The evidence in Tables 7-9 also reveal three findings. First, the positive effect of FeA is robust both in terms of significance and magnitude to controlling for exposure to shocks early in life. Similarly, the negative impacts of weather shocks on children's educational outcomes, their significance and the timing of sensitive periods are similar and robust across specifications. Lastly, for all three outcomes, the positive impact of the program is large enough to undo the disadvantage from early-life rainfall shocks. This translates into a smaller gap between children with lower endowments due to the shock and other children not affected by the shock. For example, the gap in the Icfes exam between children who were only exposed to the shocks and children only exposed to the cash transfers, is 0.23 SD (-0.10 vs. 0.13 SD in column 4). In contrast, the gap between children who experienced both the negative shock and received FeA versus children only exposed to the transfer is 0.09 SD (0.04 vs. 0.13).

6 Robustness Checks: Potential sources of selection bias

A complicating factor in the study of the impacts of early-life shocks on long-term individual outcomes is that shocks may not only have a scarring effect on affected cohorts, but may also induce selection through sorting, migration, fertility, or mortality (Almond, 2006; Bozzoli et al., 2009). Similarly, the exposure and participation to the CCT could induce migration and fertility responses that could confound the effects of the program.

In this section, we analyze whether the effects of El Niño and La Niña shocks and of the CCT induce biases of these nature.

6.1 Mobility

We define migrants as those who were born in a different municipality to where they were sampled in the Sisben data. Following this definition, we find that 30% of the sample are migrants.

Effects of El Niño and La Niña shocks Families living in weather-affected municipalities may be more likely to migrate in response to the shock. If those who migrate differ to those who stay in terms of their observable characteristics (e.g. they are less educated), this could lead to an overestimate of the effect of the weather shock on the outcome. To test for selective mobility within Colombian municipalities, we examine how rainfall affects their likelihood of migrating.

We perform a formal analysis of selective migration by estimating the effects of the shock on the probability of migration. Appendix Table A.1 shows little evidence that the shock is related to changes in migration. However, the fact that we find little evidence on the full sample does not rule out completely this concern since still there may some groups more or less likely to respond to these conditions and these specific responses are not detected in the full sample. Table A.2 explores heterogeneous migration responses by interacting exposure to the shock with observable socio-demographic characteristics. We find little evidence of differential responses.

Effects of FeA eligibility Table A.3 shows the effects of CCT eligibility on the average probability of migration for the whole sample (column 1) and heterogeneous responses (column 2). We find that eligibility to the CCT is positively associated with migration although when exploring heterogeneous responses, the only characteristic statistically significant (at the 10%) is living in smaller households (of 11 characteristics interacted with eligible). In other words, there is some evidence that eligible families with 3 or less members may be more likely to move.

6.2 Fertility

We explore the effects of exposure to negative weather shocks and of exposure to the CCT on two fertility indicators: the number of subsequent siblings and birth spacing.

Effects of El Niño and La Niña shocks Women's fertility decisions can also be affected by weather events. To test for selective fertility, we examine whether El Niño and La Niña events are associated with the number of subsequent siblings and birth spacing. As shown in Appendix Table A.4, there is no evidence of differential fertility responses between women affected and unaffected by rainfall shocks.

Effects of FeA eligibility Table A.5 shows that FeA eligibility does not impact families fertility responses, as the effect on both future fertility and birth spacing is statistically insignificant.

6.3 Mortality

The estimates of early-life shocks may also be affected by selection on mortality both at birth and during early childhood: weather shocks are likely to increase the chances of dying for those with weaker health endowment (see, for example, Almond (2006)). To test how El Niño and La Niña affect child mortality, we provide evidence on how changes in weather conditions affect the cohort size and the sex ratio, two key demographic indicators. We use Census data for 2005 as it provides information on the total population (the Sisben data only includes information on the poorest households). Consistent with the finding that there is little selective survival, results in Table A.6 show that rainfall shocks during pregnancy and early childhood are not associated with the sex ratio or the cohort size.

We also examine directly the effects of exposure to early-life weather shocks on the probability that a child dies before age 1 and before age 3. Table A.7 shows that there is no evidence that children affected by the weather shocks are more likely to die at age 1 or at age 3 (column 1). Also, we do not find differential responses by socio-demographic characteristics.

6.4 Additional Robustness Checks

Other negative shocks: exposure to violence One potential threat to the validity of our results is confounding exposure to violence shocks since Colombia faced an internal armed conflict that lasted more than 50 years. One may be worried that exposure to severe rainfall shocks during the 1990's is correlated with the occurrence and exposure to violence, which makes difficult to attribute the persistent negative effects to weather shocks.

The intense fighting between guerrilas and the paramilitary in particular during the 1980's and 1990's, as well as the proliferation of organized crime affected the wellbeing of the civilian population both in urban and rural areas. For instance, from 1980 to 2002, the homicide rate in Colombia increased from 0.2 homicides per 1,000 inhabitants to almost 0.9; and from 2002 to 2010 it decreases to a rate of 0.4 (Duque, 2016). Violence can affect children's human capital development and previous studies have linked it to negative impacts on short and long-term health, education and labor market outcomes (Brown, 2016; Camacho, 2008; Chamarbagwala and Morán, 2011; Duque, 2016; Leon, 2012).

To address this concerns, we estimate our main regressions of the interaction and add exposure to violence by controlling for average yearly homicides rate at the municipality of birth during the year before birth and from age 0-3. As shown in Appendix Table A.8, our results are robust to this alternative specification.

Selective matching across administrative datasets As in this study educational outcomes come from matching the Census of the Poor, SISBEN, with administrative records from the Ministry of Education (R-166), we must consider the extend to which selective matching could confound our estimations. In particular, we are concerned that the probability of matching is correlated with weather shocks and CCT eligibility, which could bias our results. Appendix Table A.9 shows regressions of an indicator of whether a child in the SISBEN data and born in the years of interest is found in the Ministry of Education records on exposure to rainfall shocks, CCT participation and the interaction controlling by year, month and municipality of birth fixed effects. We do not find evidence that our measures of negative shocks, human capital investments or their interaction are correlated with selective matching.

7 Conclusions

This paper provides one of the first pieces of evidence on the interaction between early-life shocks and later human capital investments exploiting a natural experiment with a regression discontinuity design for Colombia. Results show some evidence that FeA has differential effects on children who experienced early life weather shocks, in particular for appropiate grade progression. In addition, children exposed to weather shocks who also received the CCT seem to be able to overcome the adverse effects caused by El Niño and La Niña events, as well as partially catch-up with the unaffected ones who only received the transfer.

In particular, our results show that exposure to rainfall and drought events in utero and in early childhood reduced age-on-track by 2.7%, the probability of high school graduation by 2.1%, and end-of-HS-exam by 0.085 SD. In contrast, the effects of the CCT on these three outcomes were 3.9%, 17.1%, and 0.14 SD, respectively. These findings are consistent with two recent studies showing limited empirical evidence on interactions between early-life environments and subsequent human capital investments exploiting natural experiments combined with a regression discontinuity (Aguilar and Vicarelli, 2012; Malamud et al., 2016).

Our results are policy relevant in several dimensions. First, weather shocks are becoming more prevalent in developing countries threatening children's development (Hanna and Oliva, 2016). Second, CCTs represent a key component of safety nets in developing countries with 26 countries actively implementing them (World Bank, 2015). Therefore, learning about its potential mitigating impacts on certain groups is important on its own. Third, while the CCT did not fully compensate weather-affected children's educational outcomes, it seemed to have helped closing the gaps in early-life inequality.

In terms of dynamic complementarities, this paper provides little evidence in that direction. However, as discussed by Malamud et al. (2016), our reduced-form estimates are not a sufficient test that allows us to reject the presence of dynamic complementarities given that we only estimate reduced-form estimates, which only capture the net effect and does not allow us to disentangle within households endogenous responses.

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8 Figures and Tables

Figure 1: Research Design

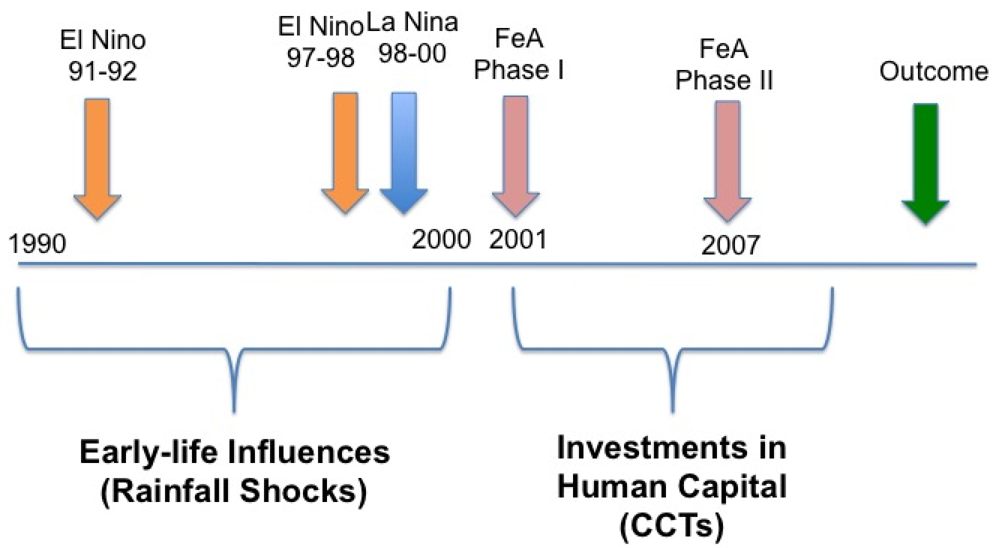
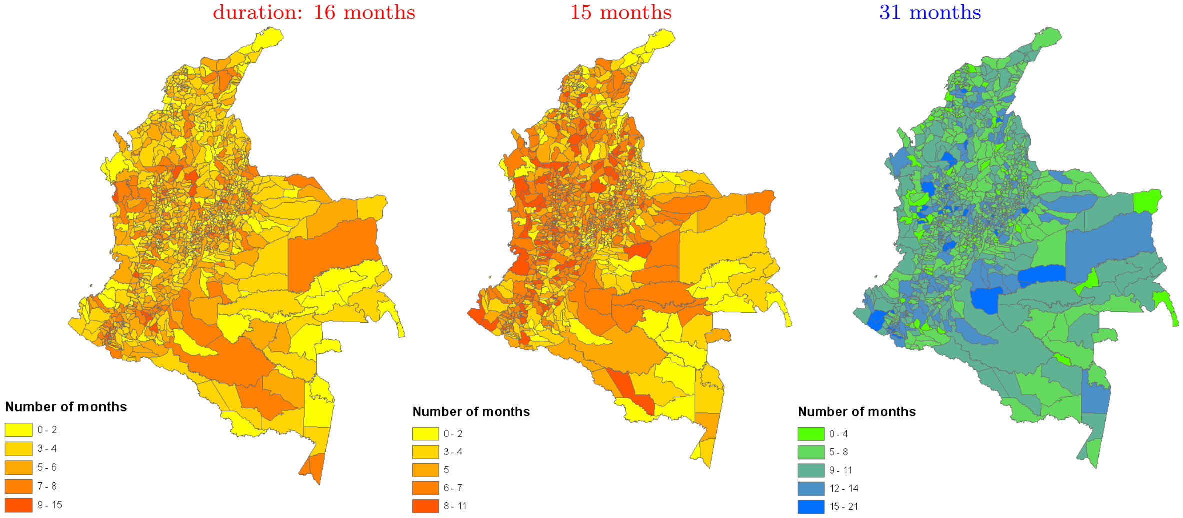


Figure 2: First Source of Variation: Weather Shocks

El Niño 1991-92 duration: 16 months

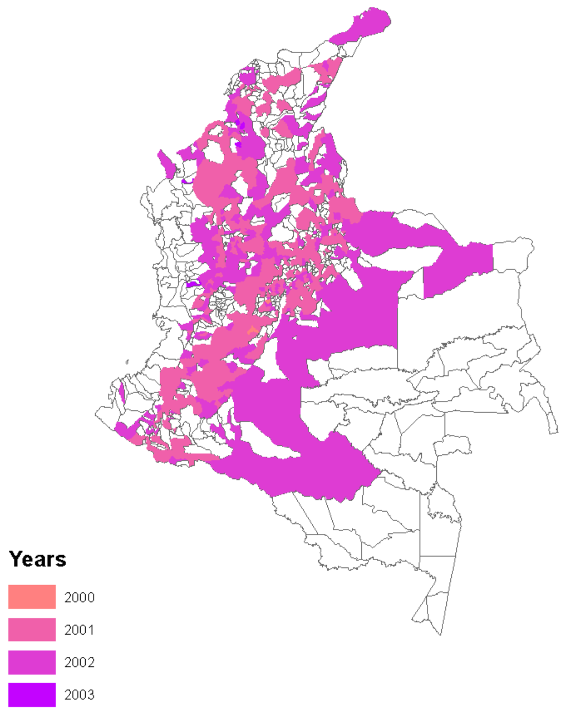
El Niño 1997-98 15 months

La Niña 1998-00 31 months



Source: Rainfall dataset CEDE, Universidad de los Andes

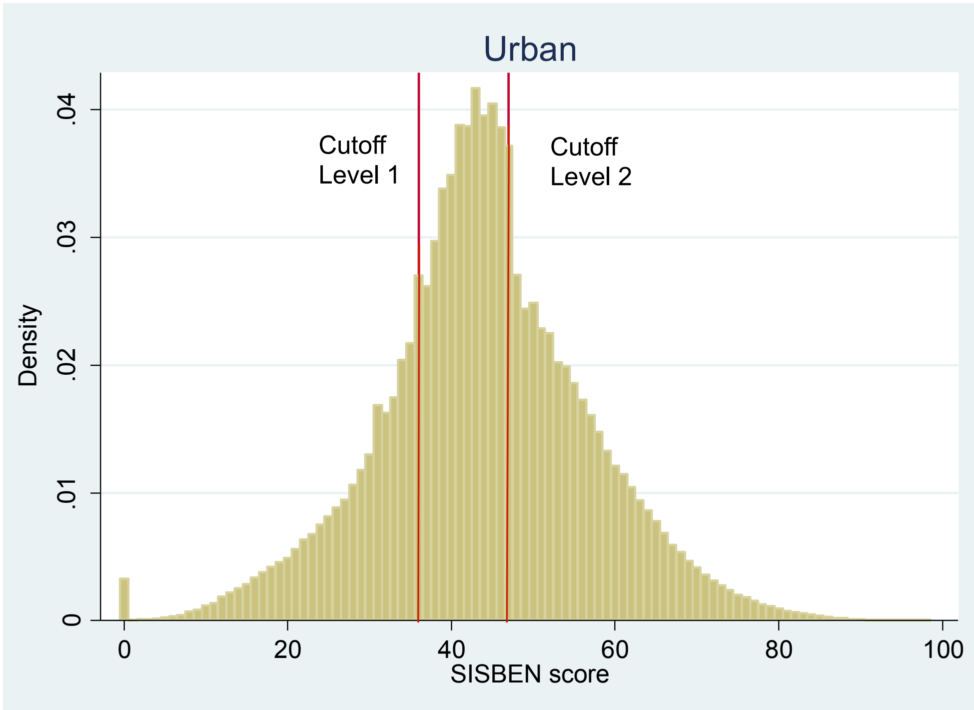
Figure 3: Roll-out of Familias en Accion - Phase I



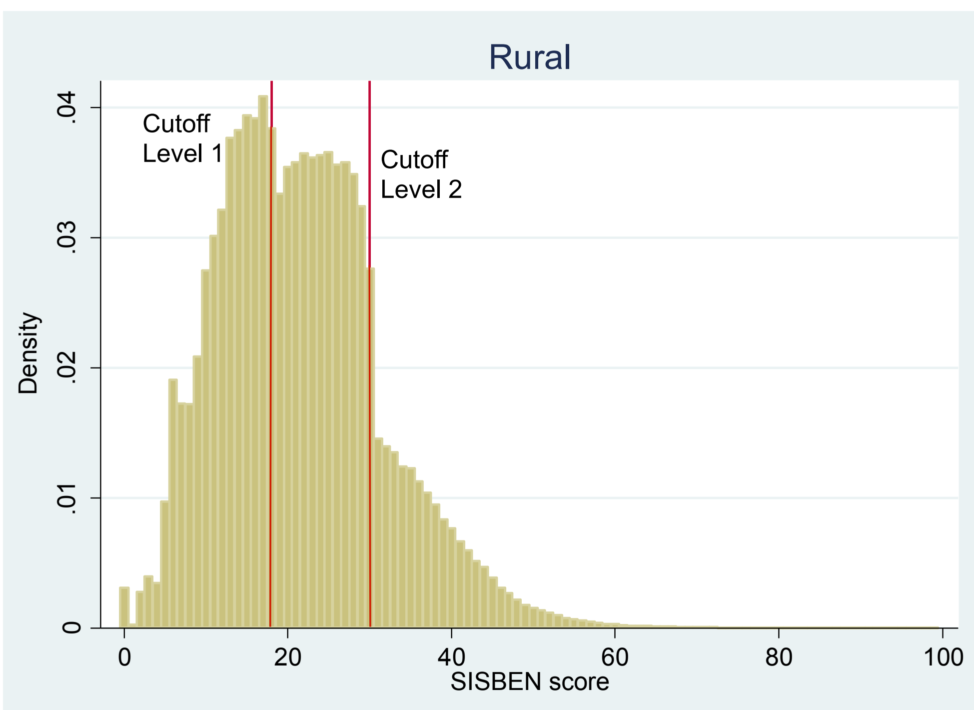
Source: Social Prosperity Ministry, Colombia

Figure 4: Imprecise Control Over the Sisben Score (Density)

Panel A: Urban

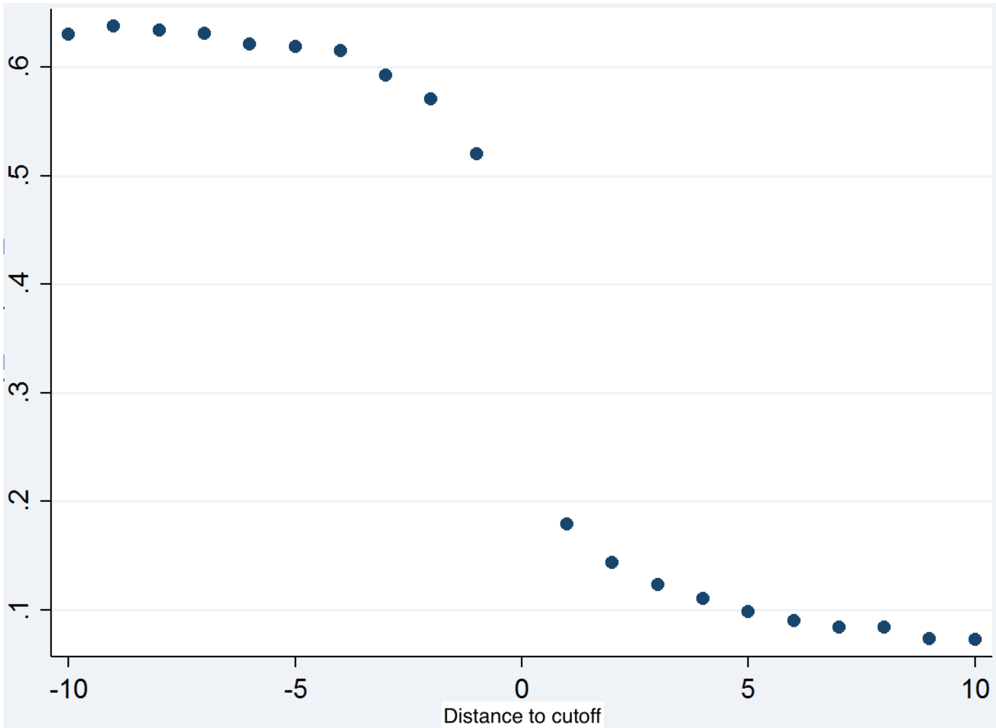


Panel B: Rural



Note: Sample includes families in the Sisben I database

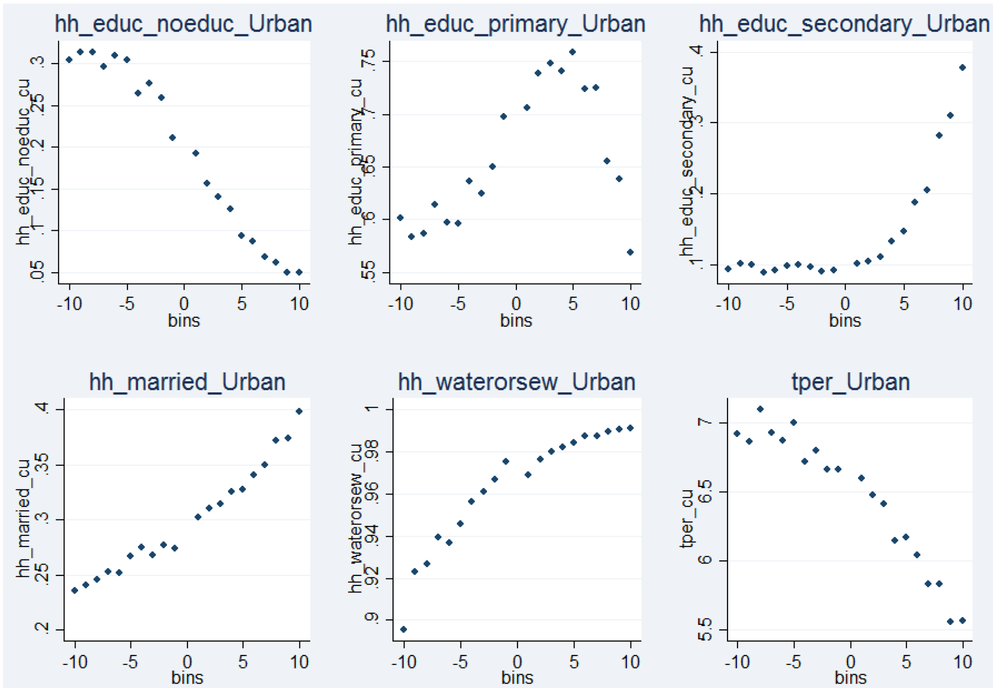
Figure 5: Participation in CCT: Imperfect Compliance



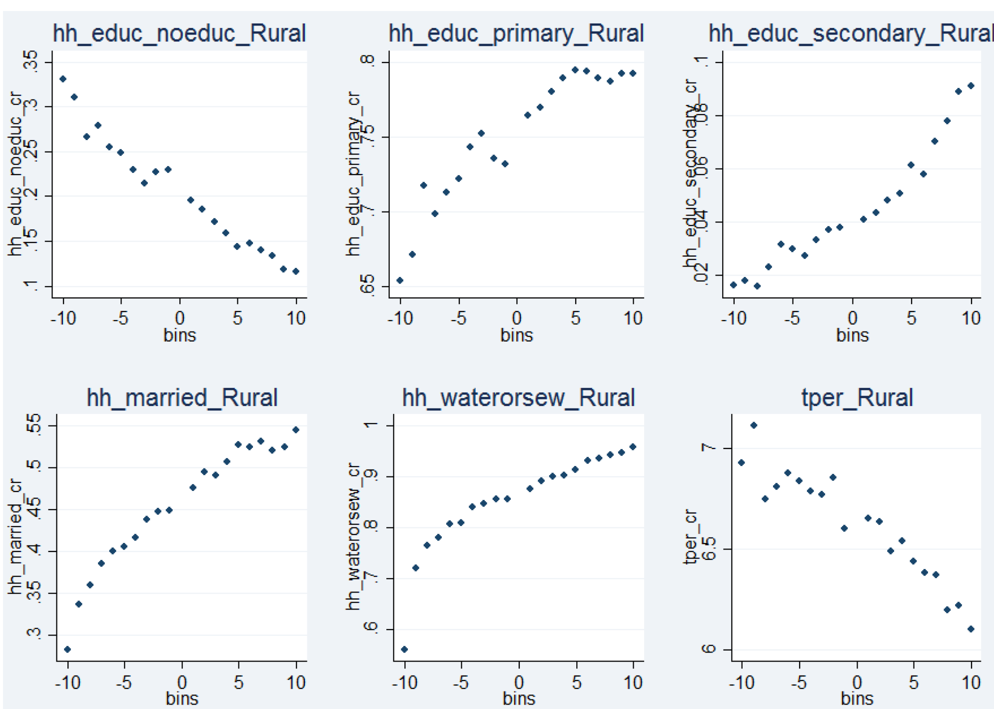
Note: Sample includes families in Sisben level 1 and level 2. Each point represents the average participation at bins of 1 point

Figure 6: Socio-demographic characteristics around the cut-off

Panel A: Urban



Panel B: Rural



Note: Sample includes families in Sisben level 1 and level 2. Each point represents the averages at bins of 1 point

Table 1: Urban and Rural SISBEN I Cutoffs

Group	Urban	Rural
1 (poorest)	0-36	0-18
2	37-47	19-30
3	48- 58	31-45
4	59-69	46-61
5	70-86	62-81
6 (less poor)	87-100	82-100

Source: Departamento Nacional de Planeacion.

Table 2: Summary statistics

	Full sample	CCT RD optimal BW sample
Household head characteristics		
Gender (female)	0.27	0.29
Age < 32	0.32	0.32
Age 33-42	0.33	0.32
No education	0.19	0.20
Primary	0.65	0.70
Married	0.31	0.29
Cohabiting	0.43	0.42
Water or sewage	0.95	0.97
HH size	6.34	6.55
	[3.20]	[3.38]
Child characteristcs		
Gender (female)	0.50	0.51
Year of birth	1995	1995
If early shock	0.87	0.87
Early shocks (months)	6.50	6.64
	[4.79]	[4.82]
Age on track	0.75	0.74
HS graduation	0.63	0.61
Icfes test score	44.45	44.30
	[5.68]	[5.67]
N	273,506	71,974

Note: "Full Sample" refers to families in Sisben level 1 and level 2. "CCT RD optimal BW sample" refer to the sample around the cutoff: 3 points below and 3 points above.

Table 3: Association between Household Characteristics and Weather Shocks

	HH head female	No education	Primary education	Married	Has access to water /sewage	HH size	Age
Shock Trimester 1	0.0020	0.0016	-0.0038	-0.00243	0.00113	0.0233	0.0976
	[0.0032]	[0.0029]	[0.0031]	[0.0030]	[0.0008]	[0.0326]	[0.0744]
Shock Trimester 2	0.0020	0.0026	-0.0008	-0.00303	-0.0012	0.0374*	0.0634
	[0.0029]	[0.0021]	[0.0032]	[0.0019]	[0.0013]	[0.0215]	[0.1367]
Shock Trimester 3	-0.0004	-0.0032	0.0041	0.0004	-0.0008	0.0051	0.0665
	[0.0038]	[0.0024]	[(0.0036]	[0.0026]	[0.0009]	[0.0199]	[0.0695]
Shock Ages 0-3	0.0018	-0.0029*	0.0033*	-0.0016	-0.0010	0.0056	0.0025
	[0.0011]	[0.0017]	[0.0018]	[0.0013]	[0.0008]	[0.0133]	[0.0436]
N	71,974	71,974	71,974	71,974	71,974	71,974	71,974

Note: Sample includes children in urban municipalities targeted by the CCT phase 1. Models include municipality, month, and year of birth FE; errors are clustered at the state level. The "Shock" variable refers to the rainfall/drought shock in the relevant period. $^{***}p < 0.01$, $^{**}\ p < 0.05$, $^{*}p < 0.1$.

Table 4: Association between Weather Shocks and CCTs

	CCT - eligible	Distance to cutoff
	(1)	(2)
Shock Trimester 1	0.001	0.0044
	[0.0048]	[0.0120]
Shock Trimester 2	0.0012	-0.0073
	[0.0036]	[0.0089]
Shock Trimester 3	-0.0001	-0.0025
	[0.0045]	[0.0121]
Shock Ages 0-3	0.0002	0.0010
	[0.0022]	[0.0062]
N (RD optimal BW)	71,914	71,914

Note: Sample includes children in urban municipalities targeted by the CCT phase 1. Models include municipality, month, and year of birth FE; errors are clustered at the state level. $^{***}p < 0.01$, $^{**}\ p < 0.05$, $^{*}p < 0.1$.

Table 5: Effects of Rainfall Shocks on Human Capital Outcomes

	Age on Track			**HS completion**			**ICFES Exam (SD)**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Shock Conception to Age 3	-0.0019***	-0.0027***		-0.0014***	-0.0023***		-0.0088***	-0.0105***	
	[0.0005]	[0.0007]		[0.0004]	[0.0008]		[0.0017]	[0.0035]	
Shock Trimester 1			0.0020			0.0007			0.0161
			[0.0031]			[0.0033]			[0.0131]
Shock Trimester 2			0.0005			-0.0045			-0.0136
			[0.0026]			[0.0035]			[0.0135]
Shock Trimester 3			-0.0048*			-0.0035			-0.0303**
			[0.0025]			[0.0033]			[0.0129]
Shock Ages 0-3			-0.0031***			-0.0027***			-0.0102***
			[0.0008]			[0.0008]			[0.0037]
N	273,506	71,974	71,974	168,099	42,915	42,915	113,283	27,994	27,994
Sample	Full	RD	RD	Full	RD	RD	Full	RD	RD
Mean	0.75	0.75	0.75	0.63	0.63	0.63			
Effect Size	-1.5%	-2.2%	-2.7%	-1.3%	-2.2%	-2.1%	-0.053	-0.063	-0.081
(@ avg shock exposure = 6m)									

Note: Sample includes children in urban municipalities targeted by the CCT phase 1. Column 1 "Full" refers to the full sample of children in Sisben level 1 (eligible) and Sisben level 2 (non-eligible). Columns 2 and 3 "RD" refer to the sample around the cutoff: 3 points below and 3 points above. Models include municipality, month, and year of birth FE; errors are clustered at the state level. Control covariates include child's gender and age, maternal education, household head education, age, family size, access to water/sewage and year of Sisben interview. The "Shock" variable refers to the rainfall/drought shock (number of months) in the relevant period. ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

Table 6: Effects of FeA on human capital outcomes

	Age on Track	**HS completion**	**Icfes Exam (SD)**
	(1)	(2)	(3)
FeA	0.0290**	0.108*	0.1382*
	[0.0148]	[0.0549]	[0.0760]
N	72,544	43,566	28,437
Mean (SD for Icfes)	0.75	0.63	1
Effect Size	3.9%	17.1%	0.1382

Note: Sample includes children in urban municipalities targeted by the CCT phase 1. Models include municipality, month, and year of birth FE; errors are clustered at the state level. Control covariates include child's gender and age, maternal education, household head education, age, family size, access to water/sewage and year of Sisben interview. "FeA" variables refers to participation in the CCT program. ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

Table 7: The Interaction between Weather Shocks and CCTs on Age on Track

	Age on Track				
	(1)	(2)	(3)	(4)	(5)
CCT	0.032**	0.032**	0.019	0.032**	0.020
	[0.015]	[0.015]	[0.017]	[0.015]	[0.017]
Shock Conception to Age 3	-0.003***		-0.003***		
	[0.001]		[0.001]		
Shock Trimester 1		0.002		0.002	0.002
		[0.003]		[0.003]	[0.003]
Shock Trimester 2		0.001		0.001	0.001
		[0.003]		[0.003]	[0.003]
Shock Trimester 3		-0.005*		-0.005	-0.004
		[0.002]		[0.004]	[0.004]
Shock Ages 0-3		-0.003***		-0.003***	-0.004***
		[0.001]		[0.001]	[0.001]
CCT * Shock Conception to Age 3			0.002*		
			[0.001]		
CCT * Shock Trimester 3				0.000	-0.003
				[0.007]	[0.007]
CCT * Shock Ages 0-3					0.002**
					[0.001]
N	71,974	71,974	71,974	71,974	71,974
Mean	0.75	0.75	0.75	0.75	0.75
Effect (Shock=Y, CCT=N)	-2.2%	-2.7%	-2.7%	-2.7%	-3.1%
Effect (Shock=N, CCT=Y)	4.3%	4.3%	-	4.3%	-
Effect (Shock=Y, CCT=Y)	2.1%	1.6%	-1.5%	1.6%	-1.9%

Note: Sample includes children in urban municipalities targeted by the CCT phase 1 at the optimal bandwidth (+/- 3 points). Models include municipality, month, and year of birth FE; errors are clustered at the state level. Control covariates include child's gender and age, maternal education, household head education, age, family size, access to water/sewage and year of Sisben interview. The "Shock" variable refers to the rainfall/drought shock in the relevant period. The bottom of the table show the implied effect size for three types of children: 1) Children who only experienced the negative "shock" at the average exposure of 6 months; 2) Unaffected children only exposed to the CCT; and 3) children who experienced both the average exposure to the rainfall shock and the CCT. These estimations add controls for average yearly homicides rate at the municipality of birth during the year before birth and from age 0-3. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

Table 8: The Interaction between Weather Shocks and CCTs on High School Graduation

	HS completion			
	(1)	(2)	(3)	(4)
CCT	0.106*	0.106*	0.104*	0.106*
	[0.056]	[0.056]	[0.056]	[0.056]
Shock Conception to Age 3	-0.002***		-0.002**	
	[0.001]		[0.001]	
Shock Trimester 1		-0.001		-0.001
		[0.003]		[0.003]
Shock Trimester 2		-0.004		-0.004
		[0.004]		[0.004]
Shock Trimester 3		0.004		0.004
		[0.003]		[0.003]
Shock Ages 0-3		-0.003***		-0.003**
		[0.001]		[0.001]
CCT * Shock Conception to Age 3			0.001	
			[0.002]	
CCT * Shock Ages 0-3				0.000
				[0.002]
N	42,915	42,915	42,915	42,915
Mean	0.63	0.63	0.63	0.63
Effect in SD (Shock=Y, CCT=N)	-2.0%	-2.1%	-2.2%	-2.0%
Effect (Shock=N, CCT=Y)	16.8%	16.8%	16.5%	16.8%
Effect (Shock=Y, CCT=Y)	14.8%	14.8%	14.3%	14.8%

Note: Sample includes children in urban municipalities targeted by the CCT phase 1 at the optimal bandwidth (+/- 3 points). Models include municipality, month, and year of birth FE; errors are clustered at the state level. Control covariates include child's gender and age, maternal education, household head education, age, family size, access to water/sewage and year of Sisben interview. The "Shock" variable refers to the rainfall/drought shock in the relevant period. The bottom of the table show the implied effect size for three types of children: 1) Children who only experienced the negative "shock" at the average exposure of 6 months; 2) Unaffected children only exposed to the CCT; and 3) children who experienced both the average exposure to the rainfall shock and the CCT. These estimations add controls for average yearly homicides rate at the municipality of birth during the year before birth and from age 0-3. $***p< 0.01$, $**\ p< 0.05$, $*p< 0.1$

Table 9: The Interaction between Weather Shocks and CCTs on the Icfes Exam (standardized)

	Icfes Exam (standardized)				
	(1)	(2)	(3)	(4)	(5)
CCT	0.140*	0.139*	0.114	0.132*	0.115
	[0.077]	[0.077]	[0.081]	[0.077]	[0.081]
Shock Conception to Age 3	-0.010***		-0.013***		
	[0.004]		[0.026]		
Shock Trimester 1		0.015		0.015	0.015
		[0.013]		[0.013]	[0.013]
Shock Trimester 2		-0.013		-0.013	-0.013
		[0.014]		[0.014]	[0.014]
Shock Trimester 3		-0.029**		-0.045**	-0.046**
		[0.013]		[0.022]	[0.023]
Shock Ages 0-3		-0.010***		-0.010***	-0.012**
		[0.004]		[0.004]	[0.005]
CCT * Shock Conception to Age 3			0.008		
			[0.010]		
CCT * Shock Trimester 3				0.050	0.055
				[0.057]	[0.057]
CCT * Shock Ages 0-3					0.006
					[0.010]
N	27,994	27,994	27,994	27,994	27,994
Mean	0	0	0	0	0
Effect in SD (Shock=Y, CCT=N)	-0.06	-0.08	-0.08	-0.10	-0.11
Effect (Shock=N, CCT=Y)	0.14	0.14	-	0.13	-
Effect (Shock=Y, CCT=Y)	0.08	0.06	-0.08	0.04	-0.11

Note: Sample includes children in urban municipalities targeted by the CCT phase 1 at the optimal bandwidth (+/- 3 points). Models include municipality, month, and year of birth FE; errors are clustered at the state level. Control covariates include child's gender and age, maternal education, household head education, age, family size, access to water/sewage and year of Sisben interview. The "Shock" variable refers to the rainfall/drought shock in the relevant period. The bottom of the table show the implied effect size for three types of children: 1) Children who only experienced the negative "shock" at the average exposure of 6 months; 2) Unaffected children only exposed to the CCT; and 3) children who experienced both the average exposure to the rainfall shock and the CCT. These estimations add controls for average yearly homicides rate at the municipality of birth during the year before birth and from age 0-3. $^{***}p< 0.01$, $^{**}\ p< 0.05$, $^{*}p< 0.1$

A Appendix

A.1 Robustness checks tables

Table A.1: Effects of Rainfall Shocks on Mobility

	Mover
Shock Trimester 1	0.0067
	[0.0057]
Shock Trimester 2	-0.0044
	[0.0078]
Shock Trimester 3	-0.0068
	[0.0045]
Shock Ages 0-3	0.0035
	[0.0022]
N	84,950

Note: Sample includes children in urban municipalities targeted by the CCT phase 1. Models include municipality, month, and year of birth FE; errors are clustered at the state level. ***$p<$ 0.01, ** $p<$ 0.05, *$p<$ 0.1.

A.2 Additional tables

Table A.2: Effects of Rainfall Shocks on Mobility

	Mover
Shock Conception to Age 3	-0.051
	[0.008]
Shock X Child is female	-0.001
	[0.001]
Shock X No edu	-0.002
	[0.001]
Shock X Primary	-0.002*
	[0.001]
Shock X Married	0.001
	[0.001]
Shock X Cohab	-0.001
	[0.001]
Shock X HH size 3 or less	0.002
	[0.002]
Shock X HH size 4-5	-0.001
	[0.001]
Shock X Water or sewage	0.005
	[0.004]
Shock X HH head female	0.003
	[0.011]
N	84,950

Note: Sample includes children in urban municipalities targeted by the CCT phase 1. Models include municipality, month, and year of birth FE; errors are clustered at the state level. $***p < 0.01$, $**\ p < 0.05$, $*p < 0.1$.

Table A.3: Effects of CCT eligibility on Mobility

	Mover	
	(1)	(2)
Eligible	0.0405*	0.0222
	[0.0202]	[0.0279]
Eligible X Child is female		-0.0121
		[0.0076]
Eligible X No edu		0.0252
		[0.0173]
Eligible X Primary		0.01303
		[0.0128]
Eligible X Married		0.0118
		[0.0142]
Eligible X Cohab		0.0059
		[0.0142]
Eligible X HH size 3 or less		0.0248*
		[0.0141]
Eligible X HH size 4-5		0.0104
		[0.0090]
Eligible X Water or sewage		-0.0008
		[0.0157]
Eligible X HH head female		0.0030
		[0.0112]
Eligible X Age less 33		-0.0039
		[0.009]
Eligible X Age 33-42		-0.0015
		[0.0081]
N	90,198	90,198

Note: Sample includes children in urban municipalities targeted by the CCT phase 1. Models include municipality, month, and year of birth FE; errors are clustered at the state level. ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A.4: Effects of Rainfall Shocks on Fertility

	Number of younger siblings (1)	**Birth spacing (wrt younger sibling)** (2)
Shock Trimester 1	0.0016	1.7453
	[0.0057]	[9.6097]
Shock Trimester 2	0.0086	1.4399
	[0.0067]	[4.1817]
Shock Trimester 3	-0.0039	-2.8956
	[0.0045]	[5.3398]
Shock Ages 0-3	0.0035	0.6848
	[0.0022]	[1.4736]
N	84,950	43,339

Note: Sample includes children in urban municipalities targeted by the CCT phase 1. Number of younger siblings is defined as the number of siblings born after any child included in our sample of interest. Birth spacing is the number of months between a child in our sample and the next younger sibling. Models include municipality, month, and year of birth FE; errors are clustered at the state level. ***$p< 0.01$, ** $p< 0.05$, *$p< 0.1$.

Table A.5: Effects of CCT eligibility on fertility responses

	Number of younger siblings (1)	**Birth spacing (wrt younger sibling)** (2)
Eligible	0.0272	21.82
	[0.0243]	[24.64]
N	85,729	43,864

Note: Sample includes children in urban municipalities targeted by the CCT phase 1. Number of younger siblings is defined as the number of siblings born after any child included in our sample of interest. Birth spacing is the number of months between a child in our sample and the next younger sibling. Models include municipality, month, and year of birth FE; errors are clustered at the state level. ***$p< 0.01$, ** $p< 0.05$, *$p< 0.1$.

Table A.6: Effects of Rainfall Shocks on Survival (using Census 2005)

	Cohort Size			Sex Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Shock Utero-Age 3	-0.0136			0.0005		
	[0.0123]			[0.0037]		
Shock in Utero		-0.0256			-0.0016	
		[0.0176]			[0.0078]	
Shock in Trimester 1			0.0044			0.0021
			[0.0275]			[0.0157]
Shock in Trimester 2			-0.0327			0.0078
			[0.0328]			[0.0140]
Shock in Trimester 3			-0.0458*			-0.0152
			[0.0258]			[0.0152]
Shock in Ages 0-3		-0.0104	-0.0101		0.0010	0.0012
		[0.0133]	[0.0133]		[0.0041]	[0.0041]
N	20,827	20,827	20,827	20,827	20,827	20,827

Note: Sample includes all municipalities-years-months in Census 2005 and is restricted to urban areas only. Models include municipality, month, and year of birth FE; errors are clustered at the municipality level. The "Shock" variable refers to the rainfall/drought shock in the relevant period i.e., models in column 1 are measured during the in-utero and up to age 3 period. Cohort size is the defined as the total number of births in a given municipality, year, and month; Sex ratio is defined as the ratio between males versus female born in a given municipality, year, and month. Both outcomes are constructed using data from Census 2005 (downloaded from IPUMS International) and include all years from 1985 to 2002 to be consistent with our main analyses. ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A.7: Effects of Rainfall Shocks on Mortality (using DHS)

	Child died before age 1		Child died before age 3	
	(1)	(2)	(3)	(4)
Shock utero to age 3	0.0001	0.0007	0.0004	0.0005
	[0.0011]	[0.0010]	[0.0007]	[0.0010]
Shock * Mom's age <23		0.0013		0.0012
		[0.0008]		[0.0008]
Shock * Mom's age 23-26		0.0010		0.0009
		[0.0007]		[0.0007]
Shock * Mom's age 27-33		-0.0002		-0.0001
		[0.0006]		[0.0006]
Shock * Mom's educ <= primary		-0.0013		-0.0013
		[0.0010]		[0.0010]
Shock * Mom's educ <= HS		-0.0009		-0.0010
		[0.0008]		[0.0007]
Shock * Mom is cohab		0.0005		0.0007
		[0.0008]		[0.0009]
Shock * Mom is single		-0.0006		-0.0003
		[0.0007]		[0.0007]
N	13,744	13,739	13,739	13,739

Note: Sample includes all municipalities-years-months in Census 2005 and is restricted to urban areas only. Models include municipality, month, and year of birth FE; errors are clustered at the municipality level. The "Shock" variable refers to the rainfall/drought shock in the relevant period i.e., models in column 1 are measured during the in-utero and up to age 3 period. Cohort size is the defined as the total number of births in a given municipality, year, and month; Sex ratio is defined as the ratio between males versus female born in a given municipality, year, and month. Both outcomes are constructed using data from Census 2005 (downloaded from IPUMS International) and include all years from 1985 to 2002 to be consistent with our main analyses. $^{***}p<0.01$, $^{**}\ p<0.05$, $^{*}p<0.1$.

Table A.8: Main results of the interaction between rainfall shocks and FeA controlling for violence exposure

	Age on track		HS completion		ICFES score	
	(1)	(2)	(3)	(4)	(5)	(6)
CCT	0.0322**	0.0188	0.1068*	0.1045*	0.1402*	0.1151
	[0.0151]	[0.0173]	[0.0555]	[0.0558]	[0.0774]	[0.0815]
Shock Conception	-0.0027***	-0.0034***	-0.0021***	-0.0023**	-0.011***	-0.0134***
to Age 3	[0.0007]	[0.0007]	[0.0008]	[0.0011]	[0.0035]	[0.0048]
CCT*Shock Conception		0.0021*		0.0006		0.0082
to Age 3		[0.0011]		[0.0024]		[0.0104]
N	71,969	71,969	42,900	42,900	27,987	27,987

Note: Sample includes children in urban municipalities targeted by the CCT phase 1 at the optimal bandwidth (+/- 3 points). Models include municipality, month, and year of birth FE; errors are clustered at the state level. Control covariates include child's gender and age, maternal education, household head education, age, family size, access to water/sewage and year of Sisben interview. The "Shock" variable refers to the rainfall/drought shock in the relevant period. These estimations additionally control for average yearly homicides rate at the municipality of birth during the year before birth and from age 0-3. ***$p<0.01$, ** $p<0.05$, *$p<0.1$

Table A.9: Effects of weather shocks and FeA on selective attrition

	Non-missing age on track variable	
	(1)	(2)
Shock conception to Age 3	0.0008	0.0007
	[0.0020]	[0.0021]
CCT - Eligible	0.009	0.0071
	[0.0230]	[0.0254]
Shock conception to Age 3* Eligible		0.0003
		[0.0008]

Note: Sample includes children in urban municipalities targeted by the CCT phase 1 at the optimal bandwidth (+/- 3 points). Dependent variable correspond to dummy variable equals to one if a child in the SISBEN data and born in the years of interest is matched with education records from the R-166 data. Models include municipality, month, and year of birth FE; errors are clustered at the state level. ***$p<0.01$, ** $p<0.05$, *$p<0.1$