Integrating Early-Life Shocks and Human Capital Investments on Children's Education *

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Abstract

This study investigates 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 the first years of life as a natural experiment; and ii), variation in subsequent investments resulting from the availability of conditional cash transfers (CCT), which 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 and we find that, while CCTs have a larger positive effect on children's educational atainment and achievement relative to the negative effects of the weather shocks, there is little evidence on an interaction effect between CCTs and weather shocks. 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
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1 Introduction

That early-life events can have long-term impacts on education, health, and wages is now well established (Almond et al., 2017; Barker, 1992; Cunha and Heckman, 2007). Less in known, however, on whether and how conditions experienced in the early stages can interact with subsequent interventions to affect long-term outcomes. To the extent that adverse conditions cannot be prevented, a key task for researchers and policy makers is to ascertain the potential and degree for mitigation: Could investing in children's health and education help reduce gaps caused by early-life trauma?

A priori, whether early-life shocks and investments can interact remains an open question. The lack of empirical evidence on these potential interactions is in part explained by its endogenous relationship: child conditions and parental and government responses can be jointly determined with future outcomes by unobserved factors (e.g., parental preferences). Hence, to arguably provide evidence on a causal link, one would need exogenous variation in both shocks and investments affecting the same cohorts of children in two subsequent developmental periods (Almond and Mazumder, 2013).

Our paper contributes to the literature by providing causal evidence on the interaction between early-life shocks and subsequent investments in children's health and education to influence long-term educational outcomes. We use large-scale administrative data and exploit two sources of arguably exogenous variation. First, we exploit 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 as a natural experiment. Focusing on changes in weather does not only provide an exogenous shock to early-life conditions but its also policy-relevant considering that trends in global climate change suggest that extreme weather events can become more frequent and intense in the near future (Kovats et al., 2003). Second, we exploit variation in later life human capital investments resulting from the introduction of a conditional cash transfers program (CCT). CCTs have been a popular intervention in developing countries to break the cycle of poverty through incentivising parental investments in children's human capital.

Previous research has shown that exposure to weather events while in-utero and before age 5 can lead to significant declines in child's health, cognitive outcomes, and educational attainment.[1] We build on this literature by exploiting temporal and geographic variation in the El Niño droughts of 1991-1992 and 1997-1998 and La Niña floods during 1998-2000. While El Niño and La Niña are recurrent phenomena that repeat every several years in the

[1] See for instance, 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).

Pacific coast, these specific weather episodes were particularly and unexpectedly intense and long in duration, and had tremendous impacts on the socio-economic conditions of local communities (CAF, 1998; Campos et al., 2012; Carvajal et al., 1999).

Colombia's CCT program *Familias en Accion* was rolled-out just a year after the La Niña event of 2000, serving to our identification in terms of the timing of the investment shock occuring after the early-life shock. Using a regression discontinuity that exploits the assignment rule of Familias en Accion, we estimate the effects of CCTs on children's educational outcomes.

We then combine both sources of variation into a natural experiment with a regression discontinuity to examine whether CCTs helped mitigate the negative effects of the weather shocks. In particular, this framework 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 reduce the El Niño and La Niña negative effects.

Linking individual-level data across four sources of administrative records – the universe of students in public schools (from the Ministry of Education), the universe of end-of-high school exam takers (from the Institute for the Promotion of Higher Education), the universe of poor households in the country (or Sisben), and the universe of CCT beneficiaries (from the Ministry of Social Protection)–, allows us to observe long-term outcomes matched to location and exact date of birth for almost 400,000 individuals born in Colombia in the decade of the 1990s. We then merge the individual data with information on rainfall from the Colombian Institute of Meteorology and Climate Conditions (IDEAM) at the municipality-month-year levels since 1980. Our outcomes of interest include both measures of educational attainment and achievement for individuals aged 15-25 that include: i) age-appropriate grade completion (age-on track), ii) high school graduation, and iii) Icfes test score, an exam that all high school graduates take regardless of whether they intend to apply to college (i.e a high school exit exam).

We show 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 being exposed to floods or droughts in early-life reduces age-on-track and high school graduation by 3.7% and 3.3% respectively (with respect to the outcome mean), and Icfes scores by 0.10 standard deviations (SD). Results do not seem to be driven by potential sources of selection bias such as migration, fertility, or mortality. In terms of potential mechanisms, we find evidence that exposure to El Niño and La Niña is associated with significant declines in birth weight and in height-for-age suggesting that child's health is a likely pathway through which early-life shocks operate.

Second, using the regression discontinuity in Familias en Accion eligibility, we show that receiving the CCT increases age-on-track, HS graduation, and the Icfes exam score by: 5.7%, 17.3%, and 0.19 SD, respectively. Moreover, we examine the question of whether differences in the timing in which the CCT is received matters. Our research design allows us to test this at least for the outcome age-on-track that is measured for both young and old cohorts in the sample.[2] Our results show that receiving the CCT prior to age 7 (and being eligible for CCT health investments) has a more pronounced impact on the probability of being on track for age versus receiving it after (and receive CCT education) (8.7% vs. a non-statistically significant 4.7%). We also show that the effects of CCTs on education are not likely driven by selective fertility or migration responses due to the CCT roll-out. In terms of mechanisms, there is some suggestive evidence that indicates that children who receive the CCT are more likely to enroll or move to better quality schools compared to other children, which could help explain the sustained gains in education.

Last, 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 little indication of a significant interaction between weather shocks and receiving the CCT. The same is true when we estimate effects among cohorts who received the CCT earlier in their lives. We do find, however, that weather-affected children who receive Familias en Accion are able to overcome the negative effect of the weather shock as the CCT effect is strictly larger (and positive) than the negative effect, but are not able to fully catch up with CCT recipients who were not exposed to El Niño or La Niña events. In other words, the cash transfer does seem to partially close the gaps due to early-life inequality (although not fully close them).

Our study makes contributions to three bodies of work. First, this paper relates to an emerging research that has explored interactions between two shocks, and which has found mixed evidence on human capital outcomes. Using data on rainfall shocks in the birth year and exploiting the experimental design of Mexico's CCT program across villages, Aguilar and Vicarelli (2012) found that the CCT was unable to mitigate declines in children's health and cognitive development caused by the shock. In contrast, Adhvaryu et al. (2015) using similar data for Mexico, found that Progresa (its CCT actually helped remediate the effect of extreme rainfall on educational attainment among young adults by almost 80%. Gunnsteinsson et al. (2014) for Bangladesh also found that maternal and newborn vitamin A-supplementation helped prevent or even mitigate the negative effects of a tornado shock

[2]Our other outcomes, HS completion and end-of-high school test scores, are only measured for those born in the early years of the 1990s and who were therefore relatively old when to receive the CCT in their childhood.

that significantly harmed child's health. Malamud et al. (2016) for the case of Romania, found that while 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. Last, Rossin-Slater and Wüst (2015) for Denmark, examined a different but related question of 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 showed that returns were actually similar across both cases, providing some evidence of substitution impacts across investments.[3]

The second 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). Since we are just starting to learn about the long-term impacts of CCTs on human capital, our study contributes to this growing research by first showing novel evidence on the potential sustained impacts of these programs on student's learning outcomes at age 20 and on the potential for mitigation of CCTs in alleviating exogenous early-life shocks. Examining these additional benefits is relevant considering that CCTs represent a large component of the safety net budget in developing countries.

Third, our paper is also related to previous work discussing the disruptive effects of weather events on child development and on 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 literature by being one of the first papers to document the long-term impacts of weather shocks on measures of labor market productivity (i.e., test scores at age 20) 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

[3] Other studies have also found differences in the returns of positive shocks in early-life across subgroups. Bhalotra and Venkataramani (2015), for instance, found that the long-term positive impacts of the introduction of antibiotics in the U.S. in 1937 varied across Black men who were exposed to different levels of institutional segregation in their state of birth. Similarly, Aizer and Cunha (2012) 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.

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.

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 in developing countries

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 1991-92 and 1997-98 and La Niña 1998-2000

El Niño and La Niña are complex weather patterns resulting from variations in ocean temperatures in the Equatorial Pacific.[4] 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 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

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

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.[5] Since 2005, the program was expanded to include other vulnerable populations such as the forcefully displaced families[6], 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

[5] Colombia's population is 48 million.

[6] 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.

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 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.[7]

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.[8] 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 each of these sources.

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

[8]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.

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.[9] 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).[10] 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.

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 socioeco-

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

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

nomic 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.[11] To identify rainfall shocks, we focus on el Niño (droughts) and la Niña (floods) events during the 1990s. We define rainfall shocks as municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly historical mean since 1980. In other words, we consider both floods and droughts as being similar detrimental shocks for human capital formation. This categorization has been widely used in previous studies on weather conditions and climate change (Guerreiro et al., 2008; Seiler et al., 2002; Shah and Steinberg, 2016). 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.[12] 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

[11] 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.

[12] 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).

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.

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.[13] Fifty-nine

[13] 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. Forty-six percent of students graduate from high school in our sample of children in Sisben levels 1 and 2 (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 43.37 and a standard deviation of 4.80 (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 381,275 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 31% 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 85% 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 seven months of shocks during early-life (with a standard deviation of 5.61 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:

$$Y_{ijtm} = \beta_0 + \sum_{k=conception}^{k=age3} \delta_k RainfallShock_{jtm}^{k} + \beta \mathbf{X_i} + \alpha_{\mathbf{j}} + \alpha_{\mathbf{t}} + \alpha_{\mathbf{m}} + \epsilon_{\mathbf{ijtm}} \qquad (1)$$

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.[14] 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 potential spatial and time correlation, we cluster standard errors at the municipality level.[15]

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.

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

[15] 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.

Figure 5 shows program take-up by Sisben score.[16] 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.[17] Equation 2 describes the first stage:

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

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

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

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

allows us to measure the interaction between FeA and rainfall shocks:

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

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

Tables 5-7 show 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 2-6). Following the literature on early life shocks and human capital, we also examine the effects of rainfall shocks by trimester of pregnancy (column 4) and by age during early childhood (column 5).

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 first three years of life is particularly harmful across our three human capital outcomes, while exposure to weather shocks in utero is detrimental only for age-appropriate grade completion. A child exposed to El Niño and La Niña, which on average is two months of high rainfall/droughts in utero and 6 months in early childhood, experiences a 3.6% fall in the probability of adequate grade progression, a 3.3% decline in the probability of high school completion, and a 0.11 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 0.10 SD decline in the Icfes exam.

5.2 The Effects of Investments on Human Capital

Table 8 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 5.7%, increases high school completion by 17.3%, and raises the Icfes score by 0.19 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 CCT 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 data, 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.

In addition, since for the age-on-track outcome we can observe children born across all years of interest, between 1990 and 2000, we can examine whether the effects of CCT participation differ by child's eligibility to receive both the health and education grant versus those only eligible to the education transfer. To perform this analysis, we separate the sample according to child's age when the CCT was rolled-out in a municipality. Children less than age 7 are eligible to receive the health grant and then the education one, while children more than age 7 only qualify for the education transfer. Table B.5 shows that the positive effect of the CCT is larger for younger children than for older ones (8.7% vs a non-significant 4.7%)

5.3 The Interaction between Early-life Shocks and Investments

Tables 9-11 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 CCT and overall exposure to the shock from conception through age 3 (column 3), and between CCT and the significant periods of exposure (columns 4-6). 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 no evidence that the CCT has differential effects for children who experienced early-life shocks. The interaction estimates are not statistically significant for our outcomes of interests.

The evidence in Tables 9-11 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).

In addition, Table B.6 present the estimations of the interactions for age-on-track by the type of transfer children are eligible to receive. We find that the absence of interaction effects between early-life weather shocks and CCT participation holds for both younger and older children. Also, table B.6 shows that the positive effects of the CCT are concentrated in younger children.

6 Potential sources of selection bias and robustness checks

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

Appendix B presents additional robustness checks to confirm that our results are robust to different specifications and not confounded with omitted factors.

Alternative definitions of the weather shocks and CCT

First, We explore the robustness of our results to distinguishing by floods versus droughts shocks during the 1990's El Niño and La Niña shocks. Table B.1 shows that both exposure to droughts and floods in utero and during early childhood are detrimental for human capital formation. Also, the magnitudes of the estimates and the evidence of sensitive periods are similar across the two types of weather shocks. Exposure to severe droughts and floods is more harmful during the first three years of life than during the in utero period.[18] Second, we explore the robustness of our evidence to alternative definitions of the shocks. In particular, 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. Table B.2 shows that the negative effects of exposure to weather shocks are robust to this alternative definition.

In addition, we estimate the effects of the CCT program on educational outcomes using an alternative definition of participation: number of months of CCT treatment. Similar as for the case of program take-up, duration in the program is endogenous as there is imperfect compliance. Therefore, we instrument treatment dosage by exploiting variation in potential exposure to the CCT taking into account CCT roll-out date and child's age at the time of roll-out. Table B.3 reports the results from this regression. We find similar effect sizes of program impacts using duration of the treatment instead of take-up.

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

[18] Table B.1 disentangles floods versus droughts for the outcome of age-on-track. Results are similar for the other outcomes and available upon request.

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 B.4, our results are robust to this alternative specification.

6.5 Potential Mechanisms (in progress)

In this section, we study potential mechanisms by which exposure to negative weather shocks can have long-term effects on children's educational outcomes. We examine the impacts of El Niño and La Niña shocks on child's health at birth and during childhood as intermediate pathways. For this analysis, we use data from the 1995, 2000 and 2005 Demographic and Health Surveys (DHS) which contain information on child's health at birth and height-for-age (HAZ) for a National representative sample. We present effects of early-life exposure to severe rainfall shocks on both a national sample of urban households and a sample of disadvantaged families comparable to our population of interest (CCT eligible in urban areas). Table C.1 shows that exposure to weather shocks during the third trimester of pregnancy decreases birth weight by 42.65 grams per month of exposure, which corresponds to -1.3% of the mean. In addition, as shown in Table C.2, exposure to weather shocks from age 0-3, in particular at age 2, has a negative impact on child's height. We find that at the average level of exposure, child's HAZ declines by 10% of a standard deviation.

7 Conclusions

This paper analyzed the interaction between early-life shocks and later human capital investments on children's educational outcomes using large-scale data. Exploiting a natural experiment of weather shocks and a regression discontinuity design of the effects of conditional cash transfers, we found that while CCTs have overall positive impacts on children's long-term educational attainment and achievement that excede the negative effects of weather shocks, there is little evidence that CCTs are more effective among weather-affected children.

Our results are policy relevant in several dimensions. First, weather shocks are becoming more prevalent, specially in developing countries, threatening children's healthy development (Hanna and Oliva, 2016). Second, CCTs represent a large component of safety nets in developing countries, with over 20 countries actively implementing these programs across the world (World Bank, 2015). Therefore, learning about its potential mitigating impacts on certain groups is highly policy relevant. Third, while we found that CCTs did not fully compensate weather-affected children's educational outcomes, CCTs are undoubtfully helping to close gaps caused by early-life inequality.

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8 Figures and Tables

Figure 1: Research Design

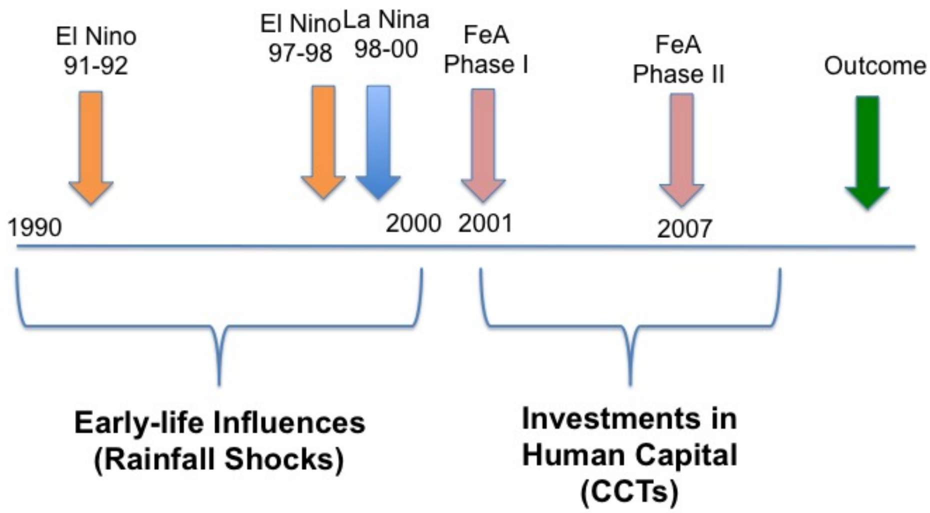
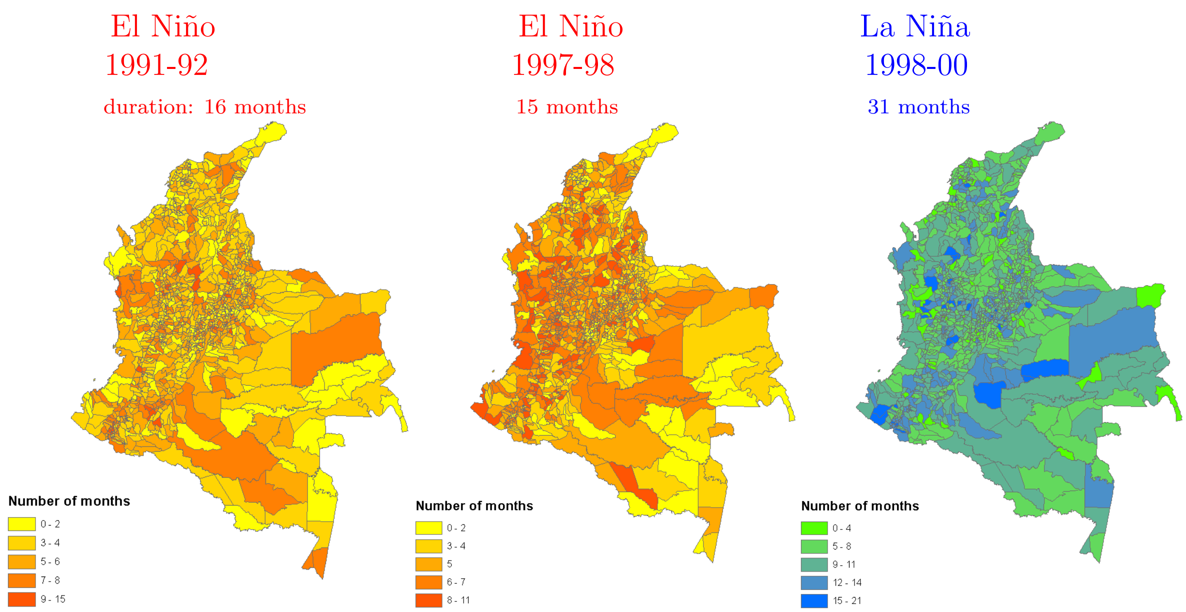
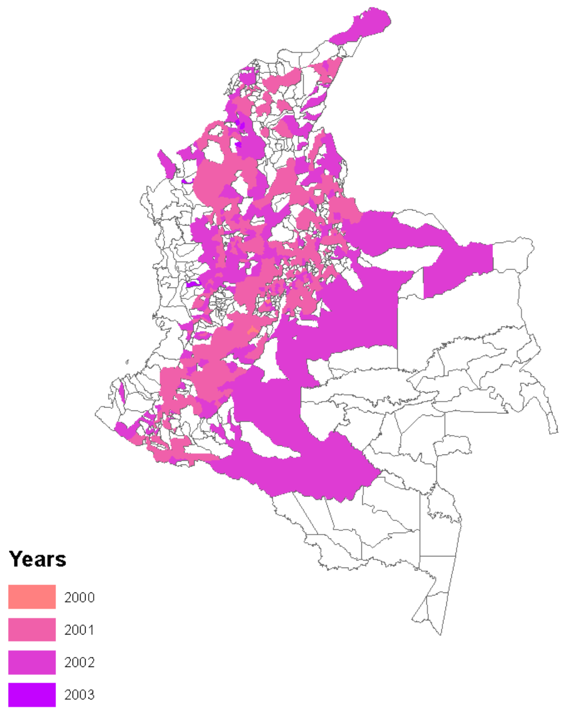


Figure 2: First Source of Variation - Weather Shocks



Note: These maps show Colombia's geographic variation in weather exposure during the events of interest. Each specific region corresponds to a municipality. The map displays the intensity of each shock measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical mean since 1980). Source: Rainfall dataset from the Colombian Institute of Meteorology and Environmental Studies, IDEAM.

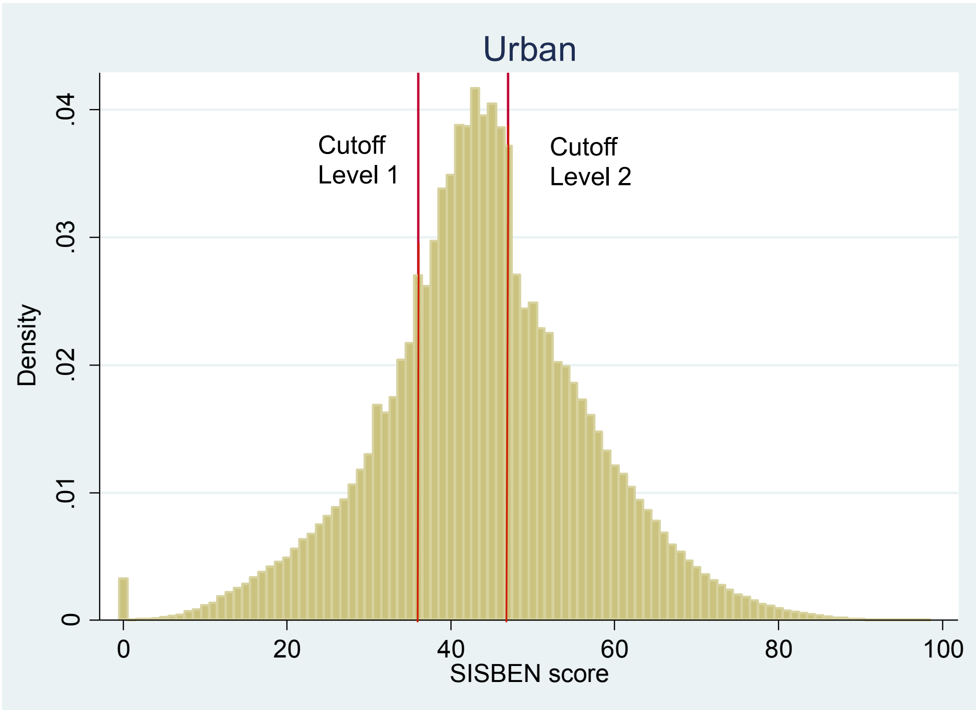
Figure 3: Roll-out of Familias en Accion - Phase I



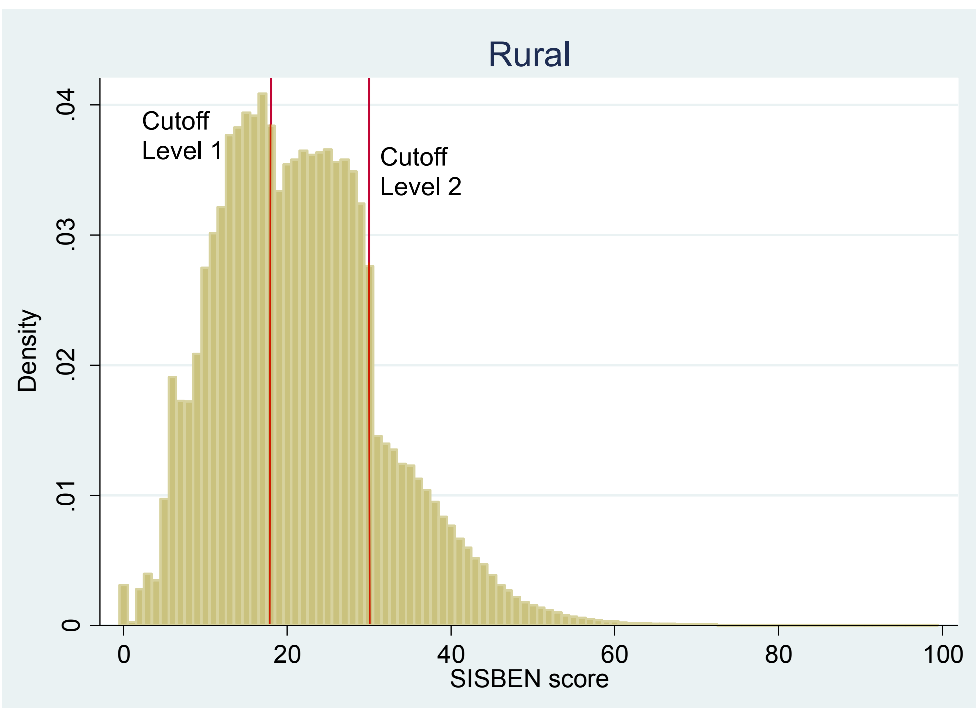
Note: Familias en Accion was initially rolled-out in municipalities with a population size no greater than 100,000 inhabitants, and with access to bank services and adequate health and schooling facilities/infrastructure. Phase I began in late 2000-early 2001. Source: Ministry of Social Protection, Colombia.

Figure 4: Sisben Score Distribution by Urban/Rural Areas

Panel A: Urban

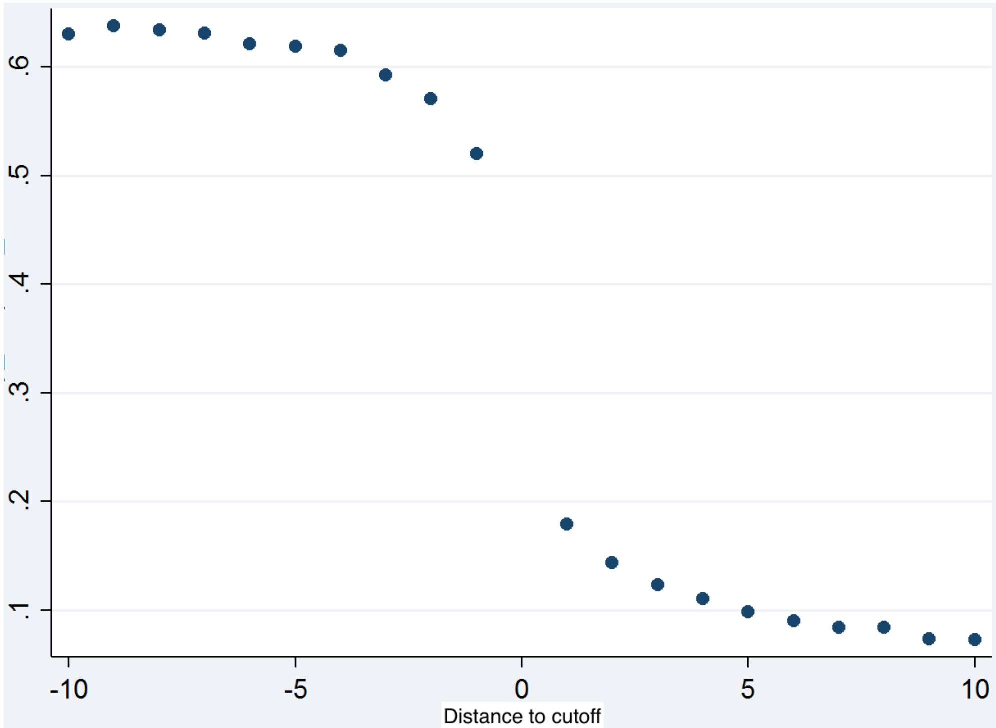


Panel B: Rural



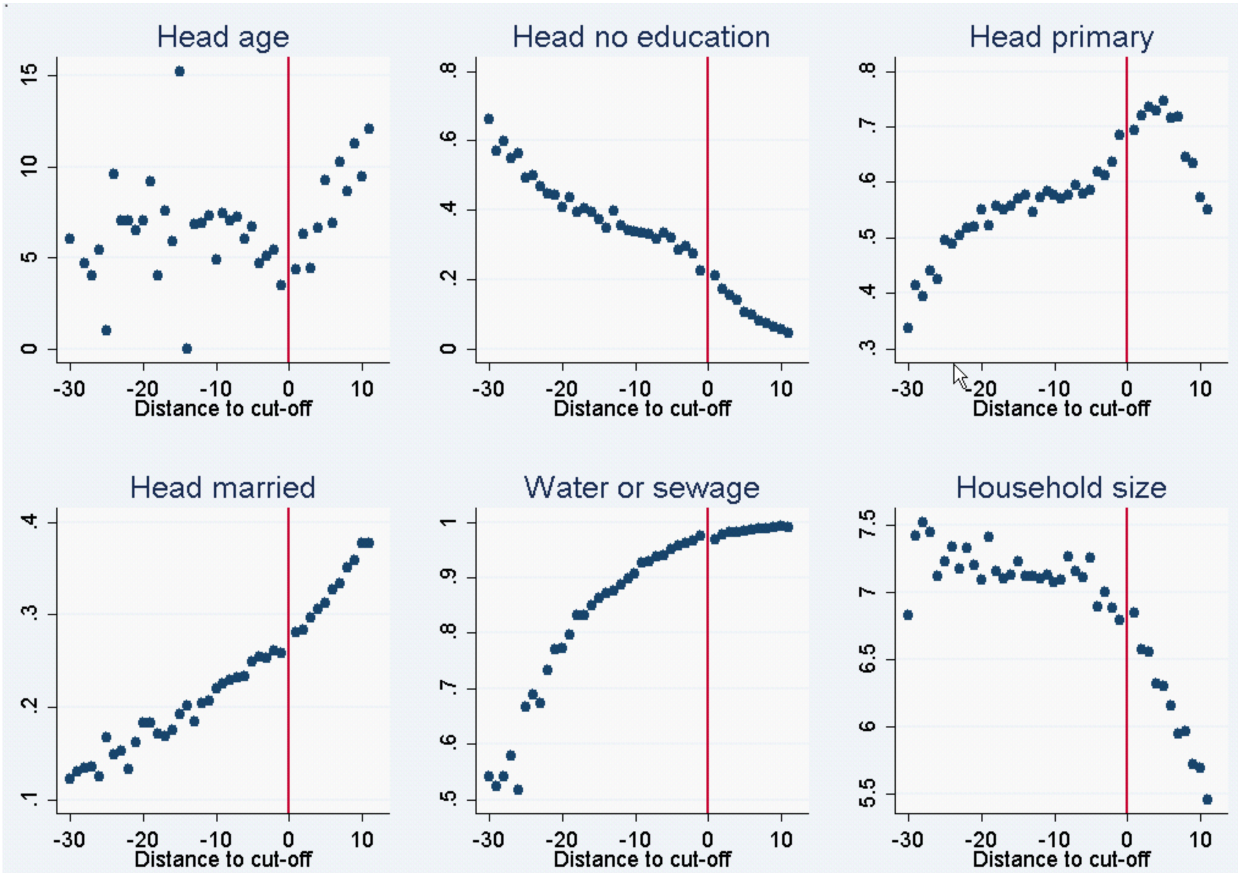
Note: Sample includes families across the whole Sisben distribution (levels 1 through 6) using the "Sisben I" (or Census of the poor) database.

Figure 5: Participation in Familias en Accion, Phase I



Note: Sample includes families in Sisben levels 1 and 2 around the cutoff of Familias en Accion eligibility. Each dot in the figure represents the average participation rate at each bin of one Sisben-score. The Sisben score is discrete and varies from 1 to 100. So, for instance, families located in the bin=-10 have a Sisben score of 26 (10 points below Familias en Accion cutoff of 36).

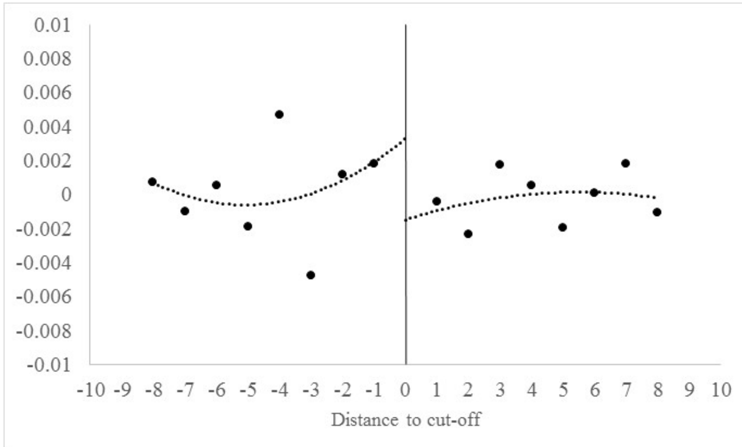
Figure 6: Socio-demographic Characteristics Around the Cutoff for Families in Urban Areas



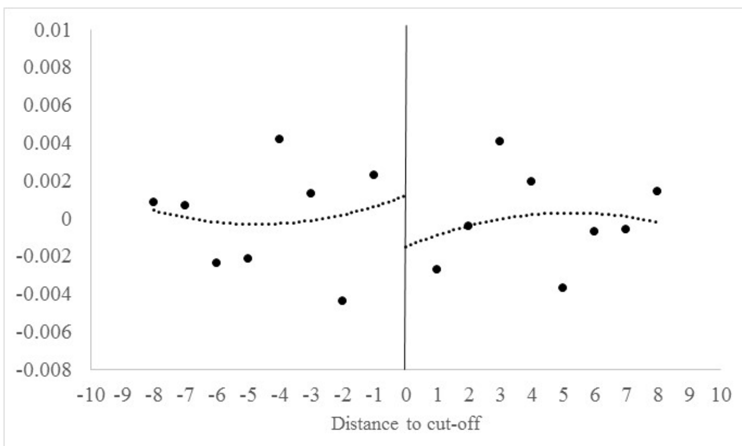
Note: Sample includes families in Sisben levels 1 and 2 around the cutoff of Familias en Accion eligibility (Sisben level 3 begins at 12 points above the cutoff and is not shown in the figures). Each dot in the figures represents the average value of each household characteristic at each bin of one Sisben-score. The Sisben score is discrete and varies from 1 to 100.

Figure 7: Educational Outcomes around the Sisben Cutoff for Familias en Accion

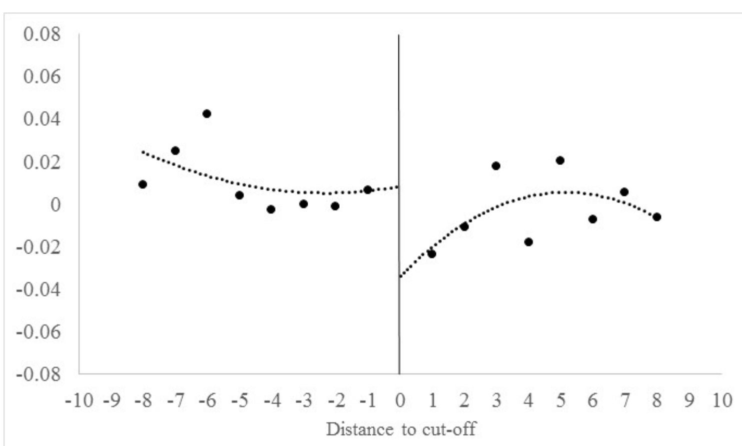
Panel A: Age-on-Track



Panel B: High School Completion



Panel C: End of High School Icfes Exam



Note: The figures show residuals from a regression of the outcome on the distance and distance squared to the Sisben cutoff (flexible on each side), and year, month, and municipaliy of birth fixed effects.

Table 1: Definition of Sisben Levels by Sisben Score in Urban and Rural Areas

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: National Planning Departament.

Table 2: Summary statistics

	Full sample (Sisben levels 1 and 2)	RD sample (optimal bandwidth)
Household head characteristics		
Gender (female)	0.27	0.29
Age less than 33	0.32	0.31
Age 33-42	0.33	0.31
Age 43-54	0.20	0.20
No education	0.19	0.20
Primary	0.65	0.70
Married	0.29	0.29
Cohabiting	0.44	0.29
Water or sewage	0.95	0.97
HH size	6.57	6.63
	[3.25]	[3.35]
Sisben score	35.93	36.60
	[8.59]	[1.72]
Eligible to CCT	0.45	0.50
Child characteristcs		
Gender (female)	0.49	0.49
Age when CCT arrived	6.70	6.55
	[2.96]	[2.96]
Exposed to early-life shock	0.85	0.85
Duration of early-life shocks (mths)	7.12	7.23
	[5.61]	[5.65]
Duration of early-life shock if exposed (mths)	8.35	8.47
	[5.16]	[5.19]
Duration of in-utero shock (mths)	1.49	1.52
	[1.93]	[1.95]
Duration of ages 0-3 shock (mths)	5.63	5.71
	[5.14]	[5.17]
Educational outcomes		
Age-on-track	0.59	0.58
HS graduation	0.46	0.55
Icfes test score	43.37	43.14
	[4.80]	[4.77]
N	381,275	102,381

Note: "Full Sample" refers to families in Sisben levels 1 and 2. "RD sample" refers to the optimal bandwidth sample around the cutoff. The period of early-life is defined as the period from in-utero up to age 3.

Table 3: Association between Weather Shocks and Household Characteristics

	Female	Age when CCT arrived	Head age <33	Head age 33-42	Head age 43-54	Head no educ	Head primary or <
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shock Trimester 1	-0.0012	-0.0200*	-0.0019	0.00	0.0021	0.0015	-0.0031
	[0.0031]	[0.0118]	[0.0025]	[0.0025]	[0.0021]	[0.0020]	[0.0024]
Shock Trimester 2	0.00328	0.0002	-0.0023	0.0017	-0.0008	0.0020	0.0002
	[0.0024]	[0.0108]	[0.0026]	[0.0026]	[0.0021]	[0.0024]	[0.0026]
Shock Trimester 3	0.00181	-0.0065	-0.0008	-0.0041	0.0021	-0.0016	0.00228
	[0.0026]	[0.0102]	[0.0028]	[0.0026]	[0.0020]	[0.0021]	[0.0025]
Shock Ages 0-1	0.00118	0.0003	-0.0009	-0.0015	0.0006	0.0008	0.00122
	[0.0013]	[0.0052]	[0.0012]	[0.0011]	[0.0010]	[0.0010]	[0.0010]
Shock Ages 1-2	0.00	-0.0051	0.0001	0.0006	-0.0006	-0.0009	0.0018
	[0.00131]	[0.0055]	[0.0014]	[0.0012]	[0.0009]	[0.0009]	[0.0011]
Shock Ages 2-3	0.0023**	-0.0043	0.0005	-0.0013	0.0001	0.0015	-0.0002
	[0.0013]	[0.0057]	[0.0013]	[0.0012]	[0.0009]	[0.0011]	[0.0013]
N	102,381	102,381	102,381	102,381	102,381	102,381	102,381

(continued...)

	Head female	Head married	Head cohabiting	HH size <4	HH size 4-5	HH size 6-7	Access to piped water or sewage
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Shock Trimester 1	0.0028	0.0016	-0.0044	-0.0008	-0.0004	0.0011	0.0006
	-0.0027	[0.0023]	[0.0028]	[0.0018]	[0.0026]	[0.0024]	[0.0007]
Shock Trimester 2	-0.0016	0.0015	-0.0008	0.0004	-0.0022	0.0012	0.00
	[0.0024]	[0.0023]	[0.0027]	[0.0015]	[0.0023]	[0.0022]	[0.0008]
Shock Trimester 3	-0.0005	0.0002	-0.0011	0.00017	0.0006	-0.0019	-0.001
	[0.0022]	[0.0025]	[0.0026]	[0.0016]	[0.0028]	[0.0026]	[0.0008]
Shock Ages 0-1	0.0005	0.0012	-0.0006	0.00014	-0.0019*	0.00	0.00
	[0.0011]	[0.0010]	[0.0012]	[0.0008]	[0.0011]	[0.0011]	[0.0003]
Shock Ages 1-2	-0.001	-0.0019*	0.0019	-0.0015*	-0.0003	-0.0009	-0.0003
	[0.0011]	[0.0011]	[0.0013]	[0.0008]	[0.0011]	[0.0011]	[0.0004]
Shock Ages 2-3	0.0009	-0.0008	-0.0003	0.0002	0.0001	-0.0004	0.0002
	[0.0012]	[0.0010]	[0.0013]	[0.0008]	[0.0013]	[0.0011]	[0.0004]
N	102,381	102,381	102,381	102,381	102,381	102,381	102,381

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 municipality 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

	Eligible for CCT	Distance to cutoff eligibility	CCT take-up
	(1)	(2)	(3)
Shock Trimester 1	-0.0009	0.0035	-0.0003
	[0.0028]	[0.0096]	[0.0026]
Shock Trimester 2	0.0005	-0.0101	-0.0033
	[0.0027]	[0.0091]	[0.0025]
Shock Trimester 3	-0.0001	0.00413	-0.0033
	[0.0024]	[0.0082]	[0.0024]
Shock Ages 0-1	0.0013	-0.0071*	-0.0010
	[0.0012]	[0.0039]	[0.0012]
Shock Ages 1-2	0.0009	-0.0036	-0.0008
	[0.0013]	[0.0049]	[0.0013]
Shock Ages 2-3	0.0014	-0.0055	-0.0007
	[0.0012]	[0.0039]	[0.0011]
N	102,381	102,381	102,381

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 Weather Shocks on Age-on-Track

	Age on Track					
	(1)	(2)	(3)	(4)	(5)	(6)
Shock Utero to Age 3	-0.0019***	-0.0026***				
	[0.0003]	[0.0005]				
Shock Utero			-0.0024***		-0.0026***	
			[0.0009]		[0.0009]	
Shock Trimester 1				-0.0019		-0.0022
				[0.0018]		[0.0018]
Shock Trimester 2				-0.0052***		-0.0056***
				[0.0017]		[0.0017]
Shock Trimester 3				-0.0000		-0.0000
				[0.0015]		[0.0015]
Shock Ages 0-3			-0.0026***	-0.0027***		
			[0.0006]	[0.0006]		
Shock Ages 0-1					-0.0050***	-0.0051***
					[0.0009]	[0.0009]
Shock Ages 1-2					0.0000	0.0000
					[0.0009]	[0.0009]
Shock Ages 2-3					-0.0025***	-0.0024***
					[0.0008]	[0.0008]
N	381,275	102,381	102,381	102,381	102,381	102,381
Sample	Full	RD	RD	RD	RD	RD
Mean	0.58	0.58	0.58	0.58	0.58	0.58
Effect size	-2.6%	-2.1%	-3.5%	-3.7%	-3.5%	-3.6%

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 through 6 "RD" refer to the optimal bandwidth 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 municipality level. Control covariates include child's gender and age in dummies, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. The "Shock" variable is measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical mean since 1980) during the events of interest (i.e., El Nino and la Nina shocks of the 1990s) in the relevant developmental stages. ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

Table 6: Effects of Weather Shocks on High School Completion

	HS completion					
	(1)	(2)	(3)	(4)	(5)	(6)
Shock Utero to Age 3	-0.0012**	-0.0013*				
	[0.0005]	[0.0008]				
Shock Utero			0.0017		0.0016	
			[0.0016]		[0.0016]	
Shock Trimester 1				0.0027		0.003
				[0.0032]		[0.0032]
Shock Trimester 2				-0.0009		-0.0009
				[0.0031]		[0.0031]
Shock Trimester 3				0.0033		0.0027
				[0.0030]		[0.0030]
Shock Ages 0-3			-0.0019**	-0.0019**		
			[0.0008]	[0.0008]		
Shock Ages 0-1					0.0003	0.0003
					[0.0014]	[0.0015]
Shock Ages 1-2					-0.0031**	-0.0031**
					[0.0013]	[0.0013]
Shock Ages 2-3					-0.0021**	-0.0021**
					[0.0010]	[0.0010]
N	210,333	54,699	54,699	54,699	54,699	54,699
Sample	Full	RD	RD	RD	RD	RD
Mean	0.55	0.55	0.55	0.55	0.55	0.55
Effect size	-1.7%	-1.9%	-2.4%	2.4%	-3.3%	-3.3%

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 through 6 "RD" refer to the optimal bandwidth 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 municipality level. Control covariates include child's gender and age in dummies, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. The "Shock" variable is measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical mean since 1980) during the events of interest (i.e., El Nino and la Nina shocks of the 1990s) in the relevant developmental stages. ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

Table 7: Effects of Weather Shocks on the Icfes (end of HS) Exam

	Icfes Exam (SD)					
	(1)	(2)	(3)	(4)	(5)	(6)
Shock Utero to Age 3	-0.0062***	-0.0103**				
	[0.0022]	[0.0043]				
Shock Utero			-0.0075		-0.0102	
			[0.0090]		[0.0090]	
Shock Trimester 1				0.0078		0.0062
				[0.0123]		[0.0124]
Shock Trimester 2				-0.0077		-0.0099
				[0.0155]		[0.0154]
Shock Trimester 3				-0.0191		-0.0236
				[0.0146]		[0.0148]
Shock Ages 0-3			-0.0109**	-0.0105**		
			[0.0042]	[0.0042]		
Shock Ages 0-1					-0.0137**	-0.0124**
					[0.0062]	[0.0062]
Shock Ages 1-2					-0.0247***	-0.0251***
					[0.0074]	[0.0074]
Shock Ages 2-3					-0.0018	-0.0014
					[0.0056]	[0.0056]
N	102,987	25,200	25,200	25,200	25,200	25,200
Sample	Full	RD	RD	RD	RD	RD
Mean	0	0	0	0	0	0
Effect size	-0.050	-0.082 SD	-0.076 SD	-0.074 SD	-0.115 SD	-0.113 SD

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 through 6 "RD" refer to the optimal bandwidth 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 municipality level. Control covariates include child's gender and age in dummies, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. The "Shock" variable is measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical mean since 1980) during the events of interest (i.e., El Nino and la Nina shocks of the 1990s) in the relevant developmental stages. ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

Table 8: Effects of Participating in CCTs on Educational Outcomes

	Age-on-Track	HS completion	Icfes Exam (SD)
	(1)	(2)	(3)
CCT - participation	0.0333**	0.0951*	0.1904**
	[0.0146]	[0.0547]	[0.0804]
N	102,381	54,699	25,200
Mean	0.58	0.55	0
Effect size	5.7%	17.3%	0.19SD

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 dummies, maternal education, household head education, age, family size, access to water/sewage and year of Sisben interview dummies. "FeA" variables refers to participation in the CCT program. ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 9: The Interaction between Weather Shocks and CCTs on Age-on-Track

	Age on track					
	(1)	(2)	(3)	(4)	(5)	(6)
CCT	0.0332**	0.0332**	0.0272*	0.0300**	0.0293*	0.0265*
	[0.0146]	[0.0146]	[0.0149]	[0.0142]	[0.0151]	[0.0148]
Shock Utero to Age 3	-0.0025***		-0.0028***			
	[0.0004]		[0.0005]			
Shock Utero		-0.0023***		-0.0031***	-0.0023***	-0.0031***
		[0.0008]		[0.0012]	[0.0008]	[0.0012]
Shock Ages 0-3		-0.0026***		-0.0026***	-0.0028***	-0.0028***
		[0.0005]		[0.0005]	[0.0006]	[0.0006]
CCT X Shock Utero to Age 3			0.0009			
			[0.0009]			
CCT X Shock Utero				0.0026		0.0024
				[0.0028]		[0.0028]
CCT X Shock Ages 0-3					0.0007	0.0006
					[0.0009]	[0.0009]
N	102,381	102,381	102,381	102,381	102,381	102,381
Mean	0.58	0.58	0.58	0.58	0.58	0.58
Effect (Shock=Y, CCT=N)	-3.4%	-3.5%	-3.9%	-3.8%	-3.7%	-4.0%
Effect (Shock=N, CCT=Y)	5.7%	5.7%	4.7%	5.2%	5.1%	4.6%
Effect (Shock=Y, CCT=Y)	2.3%	2.2%	0.8%	1.4%	1.4%	0.6%

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 through 6 “RD” refer to the optimal bandwidth 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 municipality level. Control covariates include child’s gender and age in dummies, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. The “Shock” variable is measured as the number of months of extreme weather (i.e., a municipality’s month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical mean since 1980) during the events of interest (i.e., El Nino and la Nina shocks of the 1990s) in the relevant developmental stages. The bottom of the table shows the implied effect size for three types of children: 1) Children who only experienced the weather “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 weather shock and the CCT. ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 10: The Interaction between Weather Shocks and CCTs on High School Completion

	HS completion		
	(1)	(2)	(3)
CCT	0.0948*	0.0951*	0.1031*
	[0.0547]	[0.0547]	[0.0557]
Shock Utero to Age 3	-0.0010		
	[0.0007]		
Shock Utero		0.0023	0.0023
		[0.0015]	[0.0015]
Shock Ages 0-3		-0.0016**	-0.0009
		[0.0007]	[0.0010]
CCT X Shock Ages 0-3			-0.0022
			[0.0019]
N	54,699	54,699	54,699
Mean	0.55	0.55	0.55
Effect (Shock=Y, CCT=N)		-2.0%	
Effect (Shock=N, CCT=Y)		17.3%	
Effect (Shock=Y, CCT=Y)		15.3%	

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 through 6 "RD" refer to the optimal bandwidth 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 municipality level. Control covariates include child's gender and age in dummies, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. The "Shock" variable is measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical mean since 1980) during the events of interest (i.e., El Nino and la Nina shocks of the 1990s) in the relevant developmental stages. The bottom of the table shows the implied effect size for three types of children: 1) Children who only experienced the weather "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 weather shock and the CCT. $***p < 0.01$, $** p < 0.05$, $*p < 0.1$

Table 11: The Interaction between Weather Shocks and CCTs on the Icfes Exam (standardized)

	Icfes Exam (SD)			
	(1)	(2)	(3)	(4)
CCT	0.1898**	0.1895**	0.1511*	0.1671*
	[0.0804]	[0.0804]	[0.0868]	[0.0855]
Shock Utero to Age 3	-0.0098**		-0.0131***	
	[0.0038]		[0.0048]	
Shock Utero		-0.0063		-0.0063
		[0.0063]		[0.0063]
Shock Ages 0-3		-0.0106***		-0.0131**
		[0.0041]		[0.0050]
CCT X Shock Utero to Age 3			0.0105	
			[0.0098]	
CCT X Shock Ages 0-3				0.0076
				[0.0100]
N	25,200	25,200	25,200	25,200
SD	1	1	1	1
Effect (Shock=Y, CCT=N)	-0.08	-0.07	-0.10	-0.09
Effect (Shock=N, CCT=Y)	0.19	0.19	0.15	0.17
Effect (Shock=Y, CCT=Y)	0.11	0.12	0.05	0.08

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 through 6 "RD" refer to the optimal bandwidth 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 municipality level. Control covariates include child's gender and age in dummies, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. The "Shock" variable is measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical mean since 1980) during the events of interest (i.e., El Nino and la Nina shocks of the 1990s) in the relevant developmental stages. The bottom of the table shows the implied effect size for three types of children: 1) Children who only experienced the weather "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 weather shock and the CCT. ***$p< 0.01$, ** $p< 0.05$, *$p< 0.1$

A Appendix: Selection concerns

A.1 Mobility

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. ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

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. ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

A.2 Fertility

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. ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

A.3 Survival

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: Note: Sample includes all children < 60 months of age in DHS 1995, 2000, and 2005. The sample is restricted to families living in the urban areas and to those who have not migrated since their child's conception from their municipality of interview. Models include individual covariates such as gender and age in months, mother's age, education, relationship status, and dummy for DHS wave; all models include municipality, month, and year of child's birth FE. Robust standard errors in brackets. The "Shock" variable refers to the rainfall/drought shock in the relevant period i.e., models in columns 1 and 2, it is measured during the in-utero period and up to age 1 while in columns 3 and 4 it is measured in-utero and up to age 3. ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

B Appendix: Robustness checks

B.1 Alternative definitions of the weather shocks

Table B.1: Distinguishing Droughts vs. Floods

	Age on Track		
	(1)	(2)	(3)
Floods Utero to Age 3	-0.0040***		
	[0.0009]		
Droughts Utero to Age 3	-0.0029***		
	[0.0008]		
Floods Utero		0.0028	0.0027
		[0.0018]	[0.0018]
Droughts Utero		-0.0019	-0.0020
		[0.0012]	[0.0013]
Floods Ages 0-3		-0.0054***	
		[0.0010]	
Droughts Ages 0-3		-0.0031***	
		[0.0009]	
Floods Ages 0-1			-0.0051***
			[0.0013]
Floods Ages 1-2			-0.0051***
			[0.0016]
Floods Ages 2-3			-0.0060***
			[0.0016]
Droughts Ages 0-1			-0.0041***
			[0.0011]
Droughts Ages 1-2			-0.0032***
			[0.0011]
Droughts Ages 2-3			-0.0018
			[0.0012]
N	102,381	102,381	102,381
Sample	Full	RD	RD
Mean	0.58	0.58	0.58

Note: Floods are measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above the 80th percentile of the monthly-municipality historical mean since 1980) in the relevant developmental stages, whereas droughts are measured using the 20th percentile or below. ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

Table B.2: Effects of Rainfall Shocks - Alternative Definition

Shocks measured as	Age on Track		HS completion		Icfes Exam (SD)	
+/- 1 SD	(1)	(2)	(3)	(4)	(5)	(6)
Shock Utero	-0.0014		0.0015		-0.0075	
	[0.0011]		[0.0018]		[0.0092]	
Shock Trimester 1		0.0009		0.0032		0.0182
		[0.0022]		[0.0034]		[0.0131]
Shock Trimester 2		0.0004		-0.0020		-0.0142
		[0.0020]		[0.0034]		[0.0156]
Shock Trimester 3		-0.0051***		0.0030		-0.0299*
		[0.0018]		[0.0034]		[0.0157]
Shock Ages 0-3	-0.0047***		-0.0022**		-0.0109**	
	[0.0008]		[0.0009]		[0.0047]	
Shock Ages 0-1		-0.0050***		0.0001		-0.0127*
		[0.0011]		[0.0015]		[0.0070]
Shock Ages 1-2		-0.0045***		-0.0040***		-0.0247***
		[0.0011]		[0.0015]		[0.0081]
Shock Ages 2-3		-0.0044***		-0.0022**		-0.0007
		[0.0012]		[0.0011]		[0.0065]
N	102,381	102,381	54,699	54,699	25,201	25,201
Mean	0.59	0.59	0.55	0.55	0	0
Effect size	-4.0%	-4.8%	-2.0%	-3.4%	-0.055 SD	-0.105 SD

Note: Sample includes children in urban municipalities targeted by the CCT phase 1 and in the optimal bandwidth RD 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 municipality level. Control covariates include child's gender and age in dummies, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. The "Shock" variable is measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above 1SD or below 1SD of the monthly-municipality historical mean since 1980) during the events of interest (i.e., El Nino and la Nina shocks of the 1990s) in the relevant developmental stages. ***$p<$ 0.01, ** $p<$ 0.05, *$p<$ 0.1.

B.2 Alternative definition of CCT treatment

Table B.3: The Effects of CCT Participation (in months) on Educational Outcomes

	Age on Track	HS completion	Icfes Exam (SD)
	(1)	(2)	(3)
CCT - Duration	0.0007**	0.0017	0.0033*
in months	[0.0003]	[0.0003]	[0.0017]
N	101,141	54,082	24,926
Mean (SD for Icfes)	0.58	0.55	0
Effect size	5.8%		0.16SD

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 dummies, maternal education, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. "CCT - Duration" refers to the number of months of participation in the CCT Phase 1 program instrumented by the potential exposure to the CCT (calculated using the CCT roll-out date and child's age at roll-out). ***$p<0.01$, ** $p<0.05$, *$p<0.1$.

B.3 Controlling for other negative shocks: Violence

Table B.4: Main results of the interaction between rainfall shocks and CCTs 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

B.4 Effects of age on track by age at CCT arrival

Table B.5: Effects of CCT Participation by age at roll-out

	Age on Track		
	Full sample	CCT rolled-out $<$ age 7	CCT rolled-out $>$ age 7
	(1)	(2)	(3)
CCT	0.0333**	0.0610**	0.0187
	[0.0146]	[0.0241]	[0.0164]
N	102,381	52,271	50,132
Mean (SD for Icfes)	0.58	0.7	0.44
Effect size	5.7%	4.8%	-

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 dummies, maternal education, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. "CCT - rolled-out < age 7" refers children who were age 7 or less when the CCT was rolled-out in their municipality, which imply that they are eligible to receive both the health and education grant. "CCT - rolled-out > age 7" refers children who were older than age 7 when the CCT was rolled-out in their municipality, which imply that they are eligible to receive only the education grant. ***$p< 0.01$, ** $p< 0.05$, *$p< 0.1$.

Table B.6: The Interaction Between Weather Shocks and CCTs on Age-on-track by age at roll-out

	Age on Track			
	CCT rolled out ¡ age 7		CCT rolled out ¿ age 7	
	(1)	(2)	(3)	(4)
CCT	0.0611**	0.0590*	0.0228	0.0351
	[0.0241]	[0.0323]	[0.0221]	[0.0215]
Shock Conception to Age 3				
Shock Utero	-0.0057***	-0.0060***	-0.0014**	-0.0006
	[0.0011]	[0.0016]	[0.0005]	[0.0009]
Shock Ages 0-3	-0.0046***	-0.0046***	-0.0053***	-0.0038***
	[0.0007]	[0.0009]	[0.0004]	[0.0011]
CCT * Shock Conception to Age 3				
CCT * Shock Utero		0.0012		-0.0025
		[0.0038]		[0.0037]
CCT * Shock Ages 0-3		0.0000		-0.0044
		[0.0018]		[0.0034]
N	52,271	52,271	50,110	50,110
Mean	0.7	0.7	0.44	0.44
Effect (Shock=Y, CCT=N)	-5.6%	-5.7%	-7.9%	-5.2%
Effect (Shock=N, CCT=Y)	8.7%	8.4%	-	-
Effect (Shock=Y, CCT=Y)	3.2%	2.8%	-	-

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 dummies, maternal education, household head education, age, family size, access to water/sewage, and year of Sisben interview dummies. "CCT - rolled-out < age 7" refers children who were age 7 or less when the CCT was rolled-out in their municipality, which imply that they are eligible to receive both the health and education grant. "CCT - rolled-out > age 7" refers children who were older than age 7 when the CCT was rolled-out in their municipality, which imply that they are eligible to receive only the education grant. $***p< 0.01$, $**\ p< 0.05$, $*p< 0.1$.

C Appendix: Potential mechanisms

Table C.1: Effects of Weather Shocks on Child's birth outcomes

	Birth weight (gr.)		Low birth weight	
	(1)	(2)	(3)	(4)
Shock Trimester 1	-14.77	-33.06	0.0034	0.011
	[12.79]	[27.19]	[0.0054]	[0.0106]
Shock Trimester 2	-5.97	3.95	0.0069	0.0045
	[12.67]	[28.37]	[0.0049]	[0.0104]
Shock Trimester 3	-24.79**	-42.65*	-0.0021	0.001
	[11.92]	[22.74]	[0.0043]	[0.0115]
N	6,970	1,982	6,970	1,982
Sample	Urban	Sisben	Urban	Sisben
Mean	3331.89	3322.71	5.88	6.1
Effect size (percent)	-0.7	-1.3		

Note: Sample includes all children $<$ 60 months of age in DHS 1995, 2000, and 2005. The sample is restricted to families living in the urban areas and to those who have not migrated since their child's conception from their municipality of interview. Models include individual covariates such as gender and age in months, mother's age, education, relationship status, and dummy for DHS wave; all models include municipality, month, and year of child's birth FE. Robust standard errors in brackets. The "Shock" variable refers to the rainfall/drought shock in the relevant period. ***$p<$ 0.01, ** $p<$ 0.05, *$p<$ 0.1.

Table C.2: Effects of Weather Shocks on Child's health outcomes

	Height-for-Age (Z-scores)			
	(1)	(2)	(3)	(4)
Shock Utero	-0.0171*	-0.0211		
	[0.0098]	[0.0180]		
Shock Ages 0-3	-0.0042	-0.0169*		
	[0.0061]	[0.0085]		
Shock Trimester 1			0.0007	-0.0101
			[0.0187]	[0.0291]
Shock Trimester 2			-0.0318	-0.0505
			[0.0219]	[0.0348]
Shock Trimester 3			-0.0214	-0.0039
			[0.0207]	[0.0326]
Shock Ages 0-1			-0.0002	-0.0111
			[0.0110]	[0.0158]
Shock Ages 1-2			-0.0203**	-0.0319**
			[0.0099]	[0.0131]
Shock Ages 2-3			0.0091	-0.0075
			[0.0104]	[0.0145]
N	6,903	3,801	6,903	3,801
Sample	Urban	Sisben	Urban	Sisben
Mean	-0.50	-0.58	-0.50	-0.58
Effect size	-0.02	-0.10	-0.06	-0.10

Note: Sample includes children born between 1990 and 2000 in DHS 2005. The sample is restricted to families living in municipalities targeted by the the CCT Phase I and in urban areas. Sample "Urban" refers to the full sample, while sample "Sisben" refers to the disadvantage sample targeted by the CCT. Models include individual covariates such as gender and age in months, household age, education, and relationship status; all models include municipality, month, and year of child's birth FE. Robust standard errors in brackets. The "Shock" variable refers to the rainfall/drought shock in the relevant period.
$^{***}p<0.01$, $^{**}\ p<0.05$, $^{*}p<0.1$.