How Do Early-Life Shocks Interact with Subsequent Human Capital Investments? Evidence from Administrative Data*

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Abstract

We study how early-life shocks interact with subsequent human capital investments to influence children's long-term outcomes. Using large-scale administrative data from Colombia, we combine a difference-in-difference framework with a regression discontinuity design to exploit two sources of exogenous variation: (i) early-life exposure to adverse weather shocks that affect children's initial skills and (ii), the introduction of conditional cash transfers (CCTs) that promote investments in children's health and education. We first show that early-life weather shocks reduce children's long-term outcomes, and that CCTs, in contrast, have a positive (and much larger) impact on these outcomes. Regarding their interaction, we find that when CCTs arrive in early childhood (and include a health component), the interactive effect with early-life weather shocks is negative, suggesting that the impact of the CCT is smaller for children negatively affected by weather; however, the main effect of the CCTs is large enough to mitigate the decline due to weather shocks. In contrast, when the CCT arrives at later stages (and only include an education component), both its main and interactive effects are small, suggesting that CCTs are relatively less effective to boost children's human capital and to compensate for early-life shocks.

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Data Availability: We use a confidential and deidentified version of the merged Colombian administrative datasets, which are available through several agreements between the Universidad de Los Andes and government institutions.

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1 Introduction

That early-life events can affect adult outcomes is now well-established. Lifelong health, education, and wages are all shaped by events in utero and in the early-childhood environment (Almond et al., 2017; Barker, 1990; Cunha and Heckman, 2007). To the extent that adverse shocks are difficult to predict or prevent, but at the same time, children receive investments from families, schools, and governments, a key tasks for researchers and policymakers alike is to ascertain how shocks and investments interact to influence their outcomes.

In this paper, we study how a popular social program widely implemented across the developing world – conditional cash transfers (CCTs) – can influence the human capital outcomes of children who were differentially exposed to common, yet extreme, adverse environmental shocks in their early-life. CCTs provide monetary subsidies to families with young children conditional on investments in children's human capital. Extensive research has documented their effectiveness at reducing household poverty and improving children's health and educational outcomes (Baird et al., 2014; Cahyadi et al., 2018; Fiszbein and Schady, 2009; Molina-Millan et al., 2016). Yet, whether these induced investments help undo the effects of other shocks, like weather events that are becoming more frequent and extreme due to climate change (Dell et al., 2014), is still an open and important question.

Our specific goal is to study how CCTs received at different stages in a child's life affect her long-term educational outcomes, and how these effects interact with exposure to environmental shocks during her first years of life. To explore these interactions, the paper focuses on Colombia and leverages data from multiple administrative sources. We use the universe of students in public schools, the universe of end-of-high-school exam takers, the universe of poor households in the country (denoted as *SISBEN*), and the universe of beneficiaries of Colombian's CCT program (denoted as *Familias en Acción*). Linking individuals across these administrative datasets allows us to observe long-term outcomes (up to 2015) matched to location and the exact date of birth for almost 400,000 low-income individuals born in Colombia in the 1990s (the cohorts differentially exposed to both "treatments" as children). We then merge these individual microdata with information on rainfall at the municipality-month-year level since 1980. Our outcomes of interest include both measures of educational attainment and achievement test scores that broadly capture changes in health and cognitive and noncognitive skills (Borghans et al., 2016; Borghans and Schils, 2018; Currie, 2009), which could be affected by exposure to weather shocks and the CCTs. In particular, we focus on the probability that a child remains enrolled in school, age-appropriate grade completion, and the end-of-high school exam score (ICFES), a national mandatory exam that high school graduates take regardless of whether they intend to apply to college.

Providing evidence on the interaction between weather shocks and CCTs requires that we credibly identify the individual impact of each treatment on the outcome, and that these treatments are independent from each other. We proceed as follows. First, we study the effects of weather shocks by using the temporal and geographic variation in extreme precipitation at the month-year-municipality level during the *El Niño* droughts of 1991–1992 and 1997–1998 and *La Niña* floods of 1998–2000 (see Figures 1 and 2 for the spatial and temporal variation of these shocks) to estimate a difference-in-difference (DD) model. This specification compares the outcomes of children born in the same municipality but in different months and years, and thus exposed to varying levels of extreme rainfall (i.e., floods or droughts) during these weather events. We show that being exposed to weather shocks from in utero to age 3 lowers children's education in the long term. Our estimates imply a 5% decline in the probability of a child remaining enrolled in school (relative to the outcome mean) and a 0.05-standard-deviation (SD) decline in the end-of-high school exam test score.[1] These results do not seem to be driven by potential sources of selection bias (such as mobility, fertility, or mortality). As we demonstrate in the appendix, child's health and nutritional status represent plausible mechanisms that explain the declines in educational outcomes.

To study the effects of CCTs, we use a regression-discontinuity (RD) design, which exploits eligibility for the program based on a poverty index score. Our RD strategy allows us to compare children in families on both sides of the cutoff who are similar in observable characteristics (including their likelihood of experiencing early-life shocks) except for their

[1] The magnitude of these effects are in line with previous studies on the role of negative shocks on children's human capital outcomes. We come back to this comparison in more detail in the Results Section.

eligibility for the program. We find that program participation increases the probability that a child remains enrolled in school by 10% and the end-of-high school exam score by 0.13 SD.[2]

The second step in our empirical analysis studies the interactive effects of the CCT and the weather shock. To achieve this, we combine both sources of variation into a DD-RD design (see Figure 2).[3] Our results show that the interaction coefficients are small in magnitude and highly imprecise, which limits our ability to make conclusive statements regarding differential impacts of the CCT across children differentially affected by the shock. Despite this, the (positive) estimates of the program tend to be much larger than the declines (in absolute terms) caused by the weather shock, which highlights the potential of CCTs to mitigate early disadvantage.

A key feature of the design of the program is that children below age 7 are eligible for health and nutritional investments, whereas older children only receive educational investments. We leverage this switch in induced investments by age to examine differences in the interaction between the program and the shock. Although ideally we would want to disentangle the effects of type of investment (health vs. education) from those of timing (receiving the CCT early in life versus later)[4], we can only test whether this "bundle" of investments matters for children's long-run outcomes.[5]

Our results are as follows. First, we find that the effect of the CCT program is larger for children who received it before age 7 (and thus received the health and nutrition components): they are 12% more likely to remain enrolled in school, while those who received it later

[2] Of note is that the effect on the probability of continued enrollment is measured years after a child is enrolled in the CCT program and hence, does not reflect the pure conditionality of the cash transfer but rather suggests that the program has a long-term impact on whether a child remains enrolled in school. In addition, the effect on continued enrollment is consistent to those found in previous meta analyses on the effects of CCT programs on school dropout and attendance. Because less is known about the role of these policies on learning outcomes, its harder to put our estimates in perspective of the CCT literature. We come back to this point in the Results Section.

[3] To validate this empirical strategy, we first provide evidence that experiencing the weather shocks does not affect a household's eligibility or take-up of the CCT program.

[4] Another feature related to timing is length of exposure or duration as children who received the CCTs during their early childhood have the opportunity to participate for a longer period of time.

[5] In Section 5.2.2, we provide evidence that the rollout of CCTs across municipalities is unrelated to the occurrence of *El Niño* and *La Niña* events or with changes in the socio-demographic characteristics of families across municipalities.

experienced a small and statistically insignificant increase.[6] Second, for children who received CCTs early, the interaction with the weather shock is negative and statistically significant, suggesting that the effects of the program tend to be smaller (but still positive) for those exposed to weather shocks than for the unaffected ones. According to the magnitude of the coefficient, the interaction reduces the overall impact of CCTs by a third. Thus, we conclude that while CCTs have a smaller impact on weather-affected children than on the unaffected ones, the magnitude of the main effect is such that it can overcome the adverse effects of the weather shock. Third, for children exposed to the CCT at older ages, we find a weaker interactive effect, which could partly be explained by the fact that CCT-induced investments are relatively less effective for these children to begin with (plausibly highlighting the formation of skills as a channel through which early-life shocks could be mitigated).[7] A similar pattern is observed for other educational outcomes including on-time grade completion for grades 7th, 8th and 9th.

Our paper is related to several strands of the literature. First, we contribute to the emerging reduced-form research estimating the interactive effects of human capital investments or shocks at different time periods. As discussed by Almond and Mazumder (2013), empirically testing these interactions is challenging because it requires researchers to identify at least two sources of exogenous variation inducing changes in children's skills at different stages of development. Our paper follows this strategy by connecting two policy-relevant treatments: environmental shocks and conditional cash transfers. This complements the pioneering work of interactions between CCTs and weather shocks in Mexico by Aguilar and Vicarelli (2012), which focuses on children's developmental outcomes (health and cognition) and finds little evidence on interactions, and by Adhvaryu et al. (2019), which explores long-run outcomes such as high school graduation and earnings, and finds that the interaction effect is positive and that the CCTs fully undo the adverse effects of weather.

Our study differs in important ways from those two studies. First, we focus on a much

[6] For these heterogeneous analyses by child's age of exposure to CCTs, we only focus on the first outcome (continued enrollment), as the end-of-high school exam score is (currently) only observed for the older cohorts. However, to corroborate our findings related to these heterogeneity analyses, we also examine on-time grade completion for grade 7th, 8th and 9th, which are observed for both set of cohorts.

[7] Of note is that, when we measure the effect of the CCT on the ICFES score, we are focusing on the education component of the program (given the age at which ICFES-takers were exposed to the CCT), we find sizable effects.

larger sample that includes households in urban areas, while the authors of those studies focus on rural families in Mexican villages. Second, in our CCT research design, the control group never received the treatment, while in the Mexican case, the control villages started receiving benefits 18 months after randomization, thus challenging the interpretation of long-run impacts. Third, in contrast to the previous studies that either analyze the health-induced investment of the CCT (Aguilar and Vicarelli, 2012) or the education component (Adhvaryu et al., 2019), we are able to explore heterogeneities in the interactions across these features.

Other studies in this emerging literature have examined the interactions between two policies (or positive investments) and between negative shocks and social programs (Akresh et al., 2021; Gilraine, 2017; Gunnsteinsson et al., 2014; Johnson and Jackson, 2019; Malamud et al., 2016; Rossin-Slater and Wust, 2020; Sviatschi, 2018). We contribute to this literature by focusing on a different context and population of interest, and by being the first to empirically show that interactions between shocks and investments can vary as the nature of investments vary.

Second, our paper is related to the literature on the effects of weather on human capital, which has gained particular relevance in the context of global climate change. Empirical studies in this area have demonstrated that exposure to extreme environmental episodes early in life can have detrimental effects on health, education, and wages (Aguilar and Vicarelli, 2012; Akresh et al., 2012; Baez et al., 2010; Brando and Santos, 2015; Dinkelman, 2017; Maccini and Yang, 2009; Rocha and Soares, 2015; Rosales-Rueda, 2018; Shah and Steinberg, 2017). We contribute to this line of research by showing that subsequent policy-induced human capital investments can help mitigate the effects of these shocks, particularly when they include a health component and occur early in childhood.

Third, our paper is related to the extensive research on the effects of CCTs on human capital. We add new evidence on the long-term impacts of CCTs on students' learning outcomes – an area that has received relatively less attention likely due to data limitations (Barham et al., 2018; Molina-Millan et al., 2016; Parker and Vogl, 2021). Furthermore, we complement this existing research by showing that CCTs can have potential indirect benefits for children affected by extreme weather.

Lastly, our study is related to the extensive literature on the effects of safety-net programs on human capital formation, which highlights the importance of early childhood as one of the most impactful periods for intervention (see Almond et al. (2017) for a review). Our findings underscore the importance of enhancing children's early skills to boost the benefits of subsequent interventions.

The paper is structured as follows. The next section describes the background for the empirical strategy: weather shocks and the CCT program. 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, and Section 7 concludes.

2 Background for the Empirical Strategy

2.1 Weather Shocks

The first shock to human capital we analyze is the occurrence of weather shocks, which are one of the most adverse conditions faced by households in developing countries (Dell et al., 2012; Fay et al., 2015; Hsiang and Jina, 2014), and which particularly affect children (Akresh, 2016; Bharadwaj and Vogl, 2016; Currie and Vogl, 2013; Hanna and Oliva, 2016; Sanson et al., 2019).

During the 1990s, Colombia faced three major weather events linked to *ENSO*, a recurring climate pattern associated with changes in ocean temperatures in the equatorial Pacific that disrupts weather across the globe.[8] The two opposite extreme phases of the ENSO are known as *El Niño* and *La Niña*, which manifest in different forms across geographic regions. *El Niño*, for instance, produces droughts in the northern part of South America, from Colombia to northern Brazil, whereas it causes floods and landslides in southern South America (e.g., Peru, Ecuador, Bolivia, and Chile).[9] *La Niña*, in contrast, manifests as intense floods. Their cycles vary substantially. While these events tend to repeat every 2 to 7 years, usually lasting between 9 months and 2 years, random changes in atmospheric conditions can dampen or amplify their strength, thus rendering their intensity and duration hard to predict (Climate

[8] Studies have shown that nearly 25% of the world's land surface – primarily in the tropics – faces changes in precipitation due to ENSO (Zebiak et al., 2015).

[9] It also manifests as droughts in India, Pakistan, central Indonesia, southern Philippines, the western coast of Central America, and Mexico.

Prediction Center, 2005; Kovats et al., 2003; Wittenberg et al., 2014).

The three ENSO events that we focus on were two *El Niño* (1991–1992 and 1997–1998) and one *La Niña* episodes (1998–2000). Figure 1 shows their duration as measured by the number of months in which a municipality's monthly precipitation during the windows of these events was above the 80th percentile or below the 20th percentile of the historical distribution in that municipality and month.[10] As the figure shows, even within the same decade, the geographic and temporal variation in extreme precipitation was substantial across regions and events.

The 1991–1992 *El Niño* was a "strong" drought that lasted 16 months (from April 1991 to July 1992), and which led to substantial economic losses across affected regions of the world.[11] In Colombia, it caused frequent water shortages due to the extremely low levels of water accumulation in hydroelectric dams, leading to a 12-month period of daily electricity rationing. The *El Niño* 1997–1998 drought, was regarded as a "super Niño," one of the most powerful ENSOs in recorded history. It caused a temporary increase in global air temperature of 1.5 °C, compared to the usual 0.25 °C increase of a typical *El Niño* event (Trenberth et al., 2002). The historically high temperatures led to frequent forest fires and severe droughts affecting 90% of municipalities in the country (Instituto de Hidrología, Meteorología y Estudios Ambientales, 2002)[12] and causing 1% of GDP in economic losses. After *El Niño* ended in mid-1998, it was immediately followed by a "moderate-to-strong" *La Niña* that lasted until the end of 2000. The drastic change from droughts to intense rainfall led to severe floods and landslides in areas that had previously faced the highest temperatures and most intense droughts, causing dramatic losses in agriculture and infrastructure, and large healthcare costs (International Federation of Red Cross and Red Crescent Societies, 2000).

How could the El Niño and La Niña affect children? Research has shown that exposure to severe droughts and floods can affect children's health and skill formation through dietary disruptions and malnutrition (e.g., due to agricultural losses), disease outbreaks, heat stress,

[10]This categorization has been used in previous literature on weather conditions and climate change (Guerreiro et al., 2008; Seiler et al., 2002; Shah and Steinberg, 2017).

[11]Recent research has shown that ENSO severity can explain nearly 20% of the world's annual commodity price variation (Brunner, 2002).

[12]Of the 1,100 municipalities in the country, 100 experienced extreme precipitation deficits and 861 severe deficits (Instituto de Hidrología, Meteorología y Estudios Ambientales, 2002).

and respiratory diseases. Weather shocks can also cause income declines, maternal (and family) stress, and changes in parenting quality (e.g., due to stress), which could in turn reduce parental investments in children (Aguilar and Vicarelli, 2012; Akresh et al., 2012; Baez et al., 2010; Berthelon et al., 2021; Brando and Santos, 2015; Dell et al., 2014; Kovats et al., 2003; Rocha and Soares, 2015; Rojas et al., 2014; Rosales-Rueda, 2018). Given the age-specific nature of the human capital production function, experiencing these shocks in the early stages can lead to persistent declines in long-run outcomes (Almond et al., 2017).

2.2 Conditional Cash Transfer Programs

The second shock to human capital we analyze is the introduction of the CCT program, called *Familias en Acción*.

Program description *Familias en Acción* was inspired by Mexico's *Progresa* CCT program. It began in 2001 by providing conditional subsidies to nearly 600,000 poor families to promote investments in their children's human capital. By 2004 (the end of phase I), the program had reached 622 municipalities out of the 1,100. These municipalities were selected based on five criteria: having fewer than 100,000 inhabitants, not being a department capital, having sufficient basic education and health infrastructure to absorb the new demand for social services, having a bank, and having relatively up-to-date welfare information to register new beneficiaries (Attanasio et al., 2010).[13]

The program has two components: (i) health and nutrition and (ii) education. Health and nutrition transfers are granted to mothers with children below age 7 with the intention of supplementing households' food consumption. The conditionality on the health transfer includes child vaccinations and growth development checkups, as well as mother's attendance at courses on nutrition, hygiene, and contraception. The monthly health subsidy in 2000 was US$15 (or 11% of the minimum monthly wage (m.m.w.)). Education transfers provide grants

[13] This selection of municipalities included small to medium villages and excluded large metropolitan and urbanized areas (i.e., Bogota, Medellin, etc.). According to Departamento Nacional De Planeación (2005) (p. 54), the last criterion determined whether a municipality received the program earlier versus later in Phase I. In conversations with government officials, they stated that neither the selection of municipalities to participate in the CCT program nor the timing of receiving the program responded to whether a municipality had experienced a weather shock, which we confirm in our analyses.

to mothers with children between 7 and 17 years of age with the conditionality being that the child attends at least 80% of school classes per academic year. The monthly education grant varies by school grade: For children in primary school, the subsidy was US$6 (5% of the m.m.w.), whereas for those in secondary education it was US$12 (9%). While health and nutrition subsidies are paid on a monthly basis, education subsidies follow a bimonthly scheme and only cover 10 months per year. On average, families remained enrolled in the program for 3 years (i.e., the whole duration of the initial phase).

By the end of 2005, the program was expanded to include department capitals, municipalities with more than 100,000 inhabitants, and other municipalities that were now able to offer basic health, education, and bank services. Other vulnerable populations such as the forcefully displaced families by the long-standing armed conflict also became eligible. As the program reached national coverage, the government introduced a maximum limit of 5 years for beneficiaries to receive the transfer. By 2013, the program served around three million families and its cost represented 0.8% of the national budget (Departamento Administrativo Para la Prosperidad Social, 2017).

Eligibility for the program Eligibility is based on the poverty index score from Colombia's "Census of the poor" (denoted SISBEN), which covers 60% of the country's population. This census represents the government's tool for identifying impoverished groups and therefore the mechanism through which social programs are targeted. The poverty index score on which eligibility is based ranges from 0 (poorest) to 100 (least poor) and is calculated from the first principal component of a number of variables related to household socioeconomic status, including education, family size, consumption of durable goods, current income, etc. Based on this poverty index score, households are divided into six welfare-level groups (denoted *SISBEN levels*), of which the CCT program targets those in the lowest level (SISBEN Level 1); other social programs, such as subsidized healthcare or retirement pensions, cover SISBEN Levels 1 and 2. Table A.1 shows the poverty score cutoffs used to determine eligibility for the program (i.e., SISBEN level 1), which vary by whether a household lives in a rural versus urban segment of the municipality. The fact that the program only targets SISBEN level 1, while other safety-net programs target SISBEN levels 1 and 2, represents a strength of our identification strategy, since there is no change in eligibility for other programs that coincides with that for the CCT program.

How could the CCT program affect children exposed to early-life weather shocks? While there is a large literature documenting the positive short- and medium-term impacts of CCTs on children's education and health outcomes including weight, height, and school progression (Baird et al., 2014; Cahyadi et al., 2018; Fiszbein and Schady, 2009; García and Saavedra, 2017; Molina-Millan et al., 2016), little is known on whether this popular policy could help reduce other sources of disadvantage. Theoretically, one could expect CCTs to help "undo" the adverse effects of early-life weather shocks. First, the induced health investments could mitigate the adverse impacts by promoting more targeted investments in children's nutrition, enforcing regular medical check-ups, and enhancing parental knowledge on child development practices. Second, the induced education investments could ameliorate long-term losses in education by keeping children enrolled in school, reducing child labor, increasing spending on education resulting from the cash incentive (e.g., books), or by indirectly providing parents with more or better information about the returns to education, school quality, peers, etc.

Similarly, the CCT could induce changes in parental behaviors that could reinforce or compensate investments on children. For example, parents could become more "aware" of the importance of nurturing care for their child's healthy development, which in turn could increase their time- and/or quality- of investments, thus further boosting the effects of the CCT. Other parents, in contrast, may optimally decide to shift attention and investments away from their CCT-treated child to other siblings or activities that could, eventually, lower the effectiveness of CCTs (e.g., reduce home learning activities).

Since our goal in this paper is to provide empirical evidence on the potential interactions between the CCT and the weather shock, its important to mention that our reduced-form evidence captures net effects that could include dynamic complementarities as well as behavioral responses on the part of parents, students and teachers, which could amplify, ameliorate or undo those dynamics (see Goff et al. (2023) for a detail discussion).

3 Data

3.1 Administrative Data

We use several sources of administrative records: the census of the poor, data encompassing all students in Colombia's public school system, records of the end-of-high-school exam takers, and the universe of beneficiaries of CCTs. We describe these datasets below.

The census of the poor (or SISBEN) We use the first wave (cross-section) of the SISBEN, collected between 1994 and 2003 to identify potential beneficiaries of safety-net programs. SISBEN data include rich demographic and socioeconomic information on all household members including sex, age, exact date of birth, education, marital status, occupation, income, household size, dwelling characteristics, and location of the household (state and municipality), as well as the poverty index score (known as the SISBEN score, described Section 2.2). The data contain information on over 25 million individuals—the poorest 60% of the total population. These data allow us to identify both CCT-eligible and -ineligible households, prior to the introduction of the program, based on their poverty index score.

The universe of students in public schools (R-166) This is the core database of the Ministry of Education, which provides information on school progression for all students in public schools.[14] This dataset began with Resolution 166 of 2004; prior to this year, school districts were not required to report updated student information on an annual basis. The dataset provides key educational outcomes that capture a child's evolution in the school system (although it does not contain information on test scores), as well as the specific school a child attends, and yields a sample of approximately 93 million student–year observations, for approx. 15 million students. A unique advantage of the R-166 is that it includes the exact municipality of birth for each student, which is not available in other administrative datasets. We use information from 2005 to 2015.

End-of-high-school exam (ICFES exam) The end-of-high-school test (ICFES) is a national mandatory exam taken by high school seniors regardless of whether they intend to

[14] Approximately 96% of children in SISBEN Levels 1 and 2 attend a public school in Colombia.

apply to college (although for those who enter college, the exam score determines college and major entrance). The exam includes separate tests on math, Spanish, social studies, sciences, and an elective subject. We use deidentified information from all students who took it from 2005 to 2014 (approximately one million observations).

The system of CCT beneficiaries This is a longitudinal census of program participants that includes detailed information on beneficiaries' demographic and socioeconomic characteristics as well as the amount transferred ($) to a family, the type of benefit (education or health) a child receives, and the family's duration in the program (measured in months). We use data on the program's initial rollout, years 2001 to 2004, which includes records on 2.8 million individuals (or 600,000 families) living in 622 municipalities (see Figure 3).

To link individuals across datasets, the government institutions use their individual identifiers such as full names (first and middle names and fathers' and mothers' maiden names), birth dates (day, month, and year), and national ID numbers (type of document and number). We discuss the matching process in relation to our empirical design in Appendix D.4.

3.2 Rainfall Data

We use data from the Colombian Institute of Meteorology and Climate Conditions (IDEAM), which registers precipitation levels in each of the 1,100 municipalities since 1980.[15] We define rainfall shocks as whether a municipality's monthly precipitation is above the 80th or below the 20th percentile of the municipality's monthly historical distribution since 1980.[16] In other words, we consider both floods and droughts as being similarly detrimental for human capital formation. This categorization has been used in previous literature on weather conditions and climate change (Guerreiro et al., 2008; Seiler et al., 2002; Shah and Steinberg,

[15]To determine a municipality's rainfall level, we construct a weighted average of rainfall levels from the closest IDEAM stations to the municipalities, which are weighted by the distance from each station to the municipality node (or centroid). Of note is that all municipalities in our sample have at least one IDEAM rainfall station. The number of stations increases with the municipality's area and population size.

[16]Formally, we define weather shocks as

$$WeatherShock_{jtm} = 1 - \mathbb{1}\{r_{jtm} \in [P_{20}(\mu(r_{jtm})), P_{80}(\mu(r_{jtm}))]\}, \tag{1}$$

where r_{jtm} denotes the precipitation level (mm) in a given municipality j, in year t, in month m. P_{20} and P_{80} represent the 20th and 80th percentiles of the municipality's monthly historical distribution since 1980, and $\mu(r_{jtm})$ is the rainfall distribution.

2017). We also examine other definitions of weather shocks such as one standard deviation cutoffs or use droughts and floods separately. We show that our results are robust to these alternative specifications (see Appendix D.1 and its discussion in the results section). The rainfall dataset is then merged with the administrative records at the municipality–month–year level.

3.3 Period of Exposure to Early-life Shocks and Sample of Interest

Guided by the literature in developmental psychology, epidemiology, and, more recently, economics regarding sensitive periods for skill formation (Gluckman and Hanson, 2005; Heckman, 2008; Knudsen et al., 2006; Thompson and Nelson, 2001), our baseline analysis focuses on early-life exposure to shocks, defined as the in utero period (9 months before birth) and the early years (ages 0–3). Appendix Figure A.3 provides supportive evidence that these are the critical stages in our context. In additional analyses, we also consider broader periods of exposure. 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 backward 9 months from a child's month of birth in the municipality of birth. Exposure in the early years would cover the first 3 years of life (starting in the month after birth +36 months). Exposure to weather shocks refers to the number of months a child was exposed to extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation distribution) during the events of interest (i.e., the *El Niño* and *La Niña* shocks of the 1990s) from in utero to age 3.

Given our focus on how early-life conditions determine children's long-term educational outcomes, we restrict our analysis to children who were born between 1988 and 2000 in Colombia, with information on their municipality of birth, whose families belong to SISBEN level 1 (eligible to receive CCTs) or SISBEN level 2 (ineligible). We focus on these cohorts because they were exposed to the CCT program rollout early enough (i.e., previous cohorts were too old to receive the transfer) and because their early years coincided with the *El Niño* and *La Niña* events of 1991–1992, 1997–1998, and 1998–2000. As discussed in detail in Section 4.1, we restrict the sample to families living in the urban segments of CCT municipalities.

3.4 Outcome Variables

We focus on two outcome variables:

1. **Continued enrollment:** This dummy variable takes the value of one when a child is observed across all years in the data (or until he/she completes high school) and zero otherwise (i.e., if a child drops out of school).[17] This outcome is measured for everyone in the sample (years of birth: 1988–2000), with mean 57%.

2. **End-of-high-school exam score:** This continuous variable captures the average score across all individual subjects (math, language, biology, etc.) evaluated in the end-of-high-school exam. It varies between 0 and 90, with a mean of 44.47 and a standard deviation of 5.74. This outcome is measured for the "older" cohorts in the sample (years of birth: 1988–1995), as the younger cohorts had not yet taken the exam by 2014. For the analyses, the end-of-high-school exam score is standardized (mean 0, SD 1) for each exam year.

The sample of interest varies by outcome. In the case of continued enrollment, the sample contains 259,347 students in SISBEN levels 1 and 2, while the sample of end-of-high school exam contains 102,987 exam test-takers.[18]

3.5 Descriptive Statistics

Appendix Table A.2 shows summary statistics for all children born between 1988 and 2000 whose families are either eligible (SISBEN level 1) or ineligible (SISBEN level 2) to receive the CCT program. Overall, we find that children in SISBEN levels 1 and 2 (Column 1) come from disadvantaged households. Eighty-four percent live in households in which the head has primary education or less and only 30% come from families in which the parents are married. Households tend to have an average of six to seven members. Column 2 shows

[17] We use this outcome instead of "school dropout" to standardize all outcomes as "good outcomes for the child" and to facilitate interpretation across tables.

[18] Appendix Table A.8 summarizes our educational outcomes of interest, cohorts, data source and years observed.

that families around the cutoff are fairly similar to those in the full sample of eligible and ineligible families.[19]

Regarding exposure to the weather shocks of the 1990s (*El Niño* and *La Niña* events), 88% of CCT eligible and ineligible children experienced at least one month of extreme weather shocks in their early years. The median exposure to the shock, experienced by 50% of the sample, corresponds to 1 month of extreme rainfall in utero and 7 months during ages 0 to 3.

4 Methods

To examine the interactions between early-life conditions and subsequent human capital investments, we conduct our empirical analysis in two steps. First, we examine the individual effects of early-life exposure to weather shocks and CCTs on children's education. Second, we combine the two sources of variation to estimate the interactive effects between these two "treatments." We describe each of these steps next.

4.1 Individual effects of shocks and CCTs on human capital

4.1.1 The effects of weather shocks

We estimate the effects of these shocks on children's educational outcomes by using a difference-in-difference specification:

$$Y_{ijtm} = \beta_0 + \delta\, WeatherShock_{jtm} + \beta \mathbf{X_i} + \alpha_j + \alpha_t + \alpha_m + \epsilon_{ijtm}, \tag{2}$$

where Y_{ijtm} is the outcome of child i who is born in municipality j, in year t, and in month m; $WeatherShock_{jtm}$ represents the number of months a child was exposed to extreme weather shocks from in utero through age 3 depending on his/her municipality, month, and year of birth as defined in Section 3.2 and 3.3; $\mathbf{X_i}$ is a matrix that includes the sociodemographic characteristics of a child and family, such as the child's sex and baseline age and school grade

[19] As explained below, the bandwidth selector procedure proposed by Imbens and Kalyanaraman (2012) suggested an optimal bandwidth of 3 points below and above the cutoff.

(measured the first time a child is observed in the R-166 data);[20] the household head's age, education, marital status, household size, access to water and a sewer system, and year of interview fixed effects (all measured at the SISBEN interview); the terms $\alpha_j, \alpha_t, \alpha_m$ denote fixed effects for municipality, year, and month of child's birth that capture time-invariant municipality-level characteristics, seasonality of conceptions, and shocks that are common to all children born in a given year and month; and ϵ represents the random error term. To address potential spatial and time correlation, we cluster standard errors at the municipality of birth level.[21] Our coefficient of interest in equation (2) is δ, which measures the marginal effect per month of adverse weather.

The identifying assumption required to consistently estimate δ is the independence between the error term ϵ and the *WeatherShock*, after controlling for the fixed effects and covariates described above. While we cannot directly test for all potential omitted variables, we present several tests to validate our empirical strategy. First, we perform sorting tests that assess the degree to which the variation in early-life weather conditions is correlated with a child or family's sociodemographic characteristics after controlling for the temporal and geographic fixed effecs. Results in Table 1 show little evidence that families with certain observable attributes may be more likely to experience weather shocks (i.e., exposed to the events of *El Niño* and *La Niña*), which provides support for our identification strategy. Second, we analyze pre-conception trends (see Appendix Figure A.3 and Appendix Table D.3), which test if weather shock realizations prior to conception are associated with future children's outcomes. A lack of statistical significance on these coefficients suggests little evidence of spurious differential trends between children more or less affected by weather shocks, as well as little potential selection into fertility. Third, we examine the association between weather shocks and aggregate-level economic, social, and political factors – i.e., the number of basic unmet needs, the number of effective political parties, taxes per capita, the proportion of internally displaced populations by violence, average levels of education, and the GDP per capita– to test whether our treatment of interest is confounded with other

[20] The empirical model for the end-of-high school exam also includes dummies for the age at which a child takes the exam and whether a child was enrolled in a school with morning versus other shift.

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

potential shocks that could induce changes in human capital. Appendix Table A.3 shows little evidence that weather shock realizations are significantly associated with changes in socioeconomic conditions at the municipality-year level as shown by a lack of statistical significance in the coefficients, which provides additional support for our empirical design.

4.1.2 The effects of CCTs

We estimate the effects of the CCT using an RD design that exploits the discontinuity in the eligibility rule for the CCT program given by the SISBEN poverty index score. This strategy allows us to compare children in families on both sides of the cutoff who are similar in all of their observable characteristics (including their likelihood of experiencing early-life shocks) except for their eligibility for the program.

Poverty index score manipulation. A key identification assumption of the RD design is that individuals have imprecise control over their poverty index score; in other words, individuals are randomly assigned around the cutoff.[22] Camacho and Conover (2011) showed that manipulation of the poverty index score emerged in some municipalities as a result of the score algorithm being released to local officials and that this mainly occurred between SISBEN Levels 2 and 3, where the bundle of social benefits becomes more generous. The CCT-relevant cutoff is between levels 1 and 2.

To assess the potential for manipulation in the running variable, we first examine the distribution of SISBEN scores in both urban and rural areas, as shown in Figure A.1. A visual inspection provides little evidence of manipulation around the cutoff in urban areas (Panel A), however, we do find a jump in the density of families in rural areas (Panel B). To examine this potential threat more rigorously, we conduct a version of the McCrary test that is directly applicable to our case when the running variable is discrete (Frandsen,

[22] Two other important identification assumptions are (i) monotonicity—the poverty index score crossing the cutoff cannot simultaneously cause some families to take up and others to reject the cash transfer—and (ii) excludability—the poverty index score crossing the cutoff cannot impact the outcomes except through impacting the receipt of the CCT program. These assumptions imply that we are estimating a local average treatment effect for the compliers (Lee and Lemieux, 2010).

2016).[23] Our results show that we fail to reject the null hypothesis of no manipulation for urban families, while we can reject it for rural families.[24] In addition, we corroborate the no-manipulation assumption in urban areas by zooming in around the threshold. Appendix Figure A.2 shows that local polynomial fits on the left- and right-hand side of the poverty cutoff do not exhibit any jumps in the observation frequency. Based on these findings, we perform all of our analyses focusing on households in the urban segment of the municipalities. Doing so does not exclude any municipality in the sample; it mainly reduces the focus to households living in or close to the village center and thus excludes those in remote areas.

First stage Figure 4 shows evidence on the first stage of the RD design: the relationship between the poverty index score (normalized to 0 at the eligibility cutoff) and program participation. The figure indicates that (i) program participation increases by 30 percentage points (p.p.) around the cutoff; (ii) program participation among eligible households lies between 52% and 65%; and (iii) program participation among the ineligible ones lies between 3% and 20%. Given this imperfect compliance, we use a fuzzy RD design that exploits the SISBEN assignment rule as an instrument for CCT participation.[25] The first stage of the fuzzy RD is given by

$$CCT_{ijtm} = \pi_0 + \omega T_i + \lambda g(S_i - c) + \beta \mathbf{X_i} + \alpha_j + \alpha_t + \alpha_m + \upsilon_{ijtm}, \tag{3}$$

where CCT_{ijtm} represents CCT participation: This indicator takes the value of one if child i born in municipality j, year t, and month m participated in the program. T_i denotes whether a child i is eligible to participate based on whether his/her family poverty index score S_i is below the relevant cutoff point c ($T_i = 1$ if $S_i <= c$ and $T_i = 0$, otherwise). We include a parametric but flexible function, $g(\cdot)$, of a family's poverty index score relative to the cutoff.

[23] The McCrary test assumes that the running variable is continuously distributed. When the running variable is discrete, it can falsely reject the null of no manipulation. This is because "the local linear regressions that form the basis of the test rely on the number of observed support points near the threshold growing large as the sample size increases, which is the case for a continuously distributed running variable, but not a discrete one with fixed support points" (Frandsen, 2016, p. 3).

[24] According to government officials, rural areas were subject to more manipulation given their lower monitoring of SISBEN interviews, especially before election cycles.

[25] Previous studies on the effects of CCT have also used the poverty index score as an instrument for program participation (Baez and Camacho, 2011).

We perform local linear regressions and, to determine the optimal bandwidth, we employ the bandwidth selector procedure proposed by Imbens and Kalyanaraman (2012), which suggests an optimal bandwidth of 3 points below and above the poverty index cutoff.[26]

Second stage The second-stage regression in the RD design is, in turn, given by

$$Y_{ijtm} = \beta_0 + \gamma \widehat{CCT}_{ijtm} + \varphi f(S_i - c) + \beta \mathbf{X_i} + \alpha_j + \alpha_t + \alpha_m + \varepsilon_{ijtm}, \tag{4}$$

where γ is the coefficient of interest that captures the causal local average treatment effect of receiving the CCT program on children's educational outcomes. This model includes the same covariates as in Equation 3.

A potential threat to the validity of the RD design could be that families sort around the eligibility threshold. We examine this potential threat by comparing families' observable characteristics on the left and right of the eligibility cutoff. Figure 5 shows that households around the cutoff are similar in terms of household head's age, education, marital status, access to water or a sewer system, and household size, and Appendix Table A.4 provides regression estimates on these associations (controlling for geographic and temporal fixed effects), which further corroborate a lack of sorting into the program based on family observable characteristics.

4.2 Interaction between Early-Life Shocks and Investments

To estimate the interactive effects between early-life shocks and subsequent investments, we combine both sources of variation in a difference-in-difference-RD framework:

$$\begin{aligned} Y_{ijtm} = &\beta_0 + \delta \, WeatherShock_{jtm} + \gamma \widehat{CCT}_{ijtm} + \varphi f(S_i - c) \\ &+ \tau \, WeatherShock_{jtm} * \widehat{CCT}_{ijtm} + \beta \mathbf{X_i} + \alpha_j + \alpha_t + \alpha_m + \xi_{ijtm}, \end{aligned} \tag{5}$$

[26] Estimating optimal bandwidths using other methods, such as that proposed by Calonico et al. (2014), requires a continuous running variable. Since this is not our case (i.e., the poverty index score is discrete), we show estimations for alternative bandwidths (i.e., 2 and 4 poverty index score points around the cutoff), which are summarized in Appendix D.

where δ measures the impact of exposure to weather shocks in the early stages for children who did not receive the CCT program and γ measures the effect of the CCT program for those who did not suffer from early-life adverse weather. The parameter of interest, τ, captures the differential effect of the CCT program for those who experienced adverse weather conditions from in utero to age 3.[27]

A potential threat to the validity of this strategy may arise if the probability that children experience weather shocks early in life is differentially distributed around the CCT program eligibility cutoff. To address this concern, we check whether a child's exposure to weather shocks early in life affected families' probability of being eligible for the CCT, their distance to the poverty index score cutoff, or their take-up of the program. Table 2 shows little evidence that this is the case. Figure 5 further shows that households around the eligibility cutoff are exposed to similar weather conditions.[28]

Heterogeneous interactive effects by age at CCT rollout In addition to the average interactive effect estimated in equation (5), the design of the program allows us to study potential differences by program characteristics. To do so, we use the fact that the CCT-induced investment switches from health to education at age 7 in order to estimate separate regressions for children below vs. equal to or above this age. Of course, receiving the program before age 7 not only implies that a child receives the health-induced investment, but also means that the same child is younger when exposed to the program (and potentially, exposed for a longer period). Since these "treatments" could themselves have separate effects on the outcome, we cannot claim that the regression coefficients only reflect the effects of health investments. As such, our results are interpreted as the effect of the bundle of type and timing (and possibly, duration) of CCT-induced investments.

We use the program rollout across municipalities and years to identify a child's age at the time of the CCT introduction[29] and as outcome, we focus on the probability of continued

[27]Note that the estimated model includes two endogenous variables: $\{CCT_{ijtm}, WeatherShock_{jtm}^{Utero\_Age3} \times CCT_{ijtm}\}$, for which we use two instruments: $\{T_i, WeatherShock_{jtm}^{Utero\_Age3} \times T_i\}$.

[28]To the best of our knowledge, there is no evidence that the CCT program has been used as a platform to distribute aid to families in times of extreme weather shocks.

[29]We do not use a child's age when first observed as a CCT-beneficiary because this is an endogenous decision from a family's perspective.

enrollment, which, in contrast to the Icfes score, can be observed for children who were younger and older than age 7 at the time of the CCT rollout.

We validate the use of the CCT rollout as a source of variation by testing whether the timing of the rollout was associated with household characteristics. In Appendix Table A.5 we report these coefficients, which suggest that families were not differentially exposed to the program earlier versus later according to their observable characteristics (age, education, etc.). More importantly, the table also shows that the timing of the CCT rollout is not correlated with experiencing the weather shocks (column 9).

5 Results

5.1 Individual effects of shocks and CCTs on human capital

We begin by documenting that both weather shocks and CCTs have separate and significant effects on human capital. Then, we use both treatments to test the interactive model.

5.1.1 The effects of weather shocks

Table 3 presents the estimates of early-life weather shocks on children's outcomes using equation (2). Columns (1) and (3) show the effects for the full sample of children in poverty (i.e., in SISBEN levels 1 and 2), and columns (2) and (4) for those in the optimal RD bandwidth—3 points above and below the program eligibility cutoff. To enhance the interpretability of these coefficients, the table also reports the results of scaling the marginal effects per month of exposure by the variation in the weather-shock distribution from the 25th percentile to the 75th, which is 8 months. Results indicate that a child exposed to this duration experiences a 5.0% decline in the probability of continued enrollment (with respect to the outcome mean) and a 0.05 SD decline in test scores.[30] In the Robustness Section 6, we provide evidence that these effects are robust to using alternative definitions of weather

[30] While households living in rural and remote areas of the municipalities are not part of our analytic sample, we find that exposure to adverse weather decreases the probability that a child remains in school by 5.4% and reduces test scores by 0.06 SD, suggesting that weather shocks have similar effects on children in rural and urban areas.

shocks.[31]

Magnitudes. While the influential work by Maccini and Yang (2009) showed that moderate increases in rainfall have a positive effect on long-term outcomes in the Philippines, there are actually few empirical studies examining the impacts of early childhood exposure to extreme weather shocks on long-term outcomes. Two of the few examples are: Dinkelman (2017), that found that extreme droughts in childhood were associated with a 5% increase in the incidence of adult disability at age 23 using data from South Africa, and Akresh et al. (2012), who found that in utero rainfall shocks in Burkina Faso led to a 0.24 SD decline in the Raven ability test at age 9. In terms of the literature of early-life exposure to extreme shocks more broadly, our results are consistent in magnitude with those focusing on developing countries. For instance, Duque (2017) found that children in low-educated families (similar to those in our sample) who were exposed to violence in Colombia in their early stages experienced a 0.20 SD decline in the ICFES exam. Bleakley (2007) found that children infected by hookworm in the U.S. in the early 1900s (a comparable setting to a developing country now) were 20% less likely to attend school.

Mechanisms. A natural question that arises is how exposure to early-life weather shocks could influence later-in-life human capital outcomes. To provide evidence of potential mechanisms, we use several sources of auxiliary data including the Demographic and Health Surveys, Population Census, the Vital Statistics Birth Records, and the baseline wave of the *Familias en Acción* household survey (see Attanasio et al., 2004; García and Hill, 2010). Using a similar difference-in-difference framework as equation (1), we find that after exposure to the El Niño and La Niña events: i) families face a temporal decline in their income and food consumption (Appendix Tables B.1 and B.2); ii) children are more likely to be born low-birth-weight and have lower height-for-age during early childhood (Appendix Ta-

[31] In particular, we tested the following specifications: (i) including other thresholds of rainfall shock exposure (i.e., changes in precipitation between the 60th and 80th percentiles and between the 20th and 40th percentiles); (ii) separating the shocks between droughts and floods; and (iii) using different cutoffs to define extreme weather (+/- one standard deviation instead of the upper 80th or the lower 20th percentile). These results are reported in Table D.1.

bles B.3-B.4); and iii), young adults are significantly shorter (height) compared to their weather-unaffected peers (Appendix Table B.4). Taken together, these findings suggest that deterioration of nutritional investments and infant health represent relevant pathways underlying the persistent effects of early-life weather shocks in our context. While there may be (many) other relevant mechanisms at play (e.g., maternal stress, child's early skills), we lack data to empirically analyze these and thus rely on previous studies to guide the discussion (see Section II).

5.1.2 The effects of CCTs

Tables 4 and 5 show estimates of receiving the CCT on children's education using equation (4).[32] Column (1) of Table 4 indicates that children who participate in the program experience an increase in the probability of continuing in school of 9.5%. Column (1) of Table 5 shows that the program increases test scores by 0.13 SD.[33]

Magnitudes. Our effects are within those found in previous research. For instance, García and Saavedra (2017) in their meta-analysis of 47 CCT programs across the world found that, on average, these interventions reduce school dropout by 3 pp (our intent-to-treat (ITT) estimate suggests a decline of 3.6 pp). Much less is known regarding how CCTs affect student achievement (Molina-Millan et al., 2016). While some studies have found positive effects on test scores (e.g., Barham et al., 2018), others have shown little gains on student learning (Baez and Camacho, 2011). Because the CCT promotes school attendance and increases school completion for those who, in the absence of the program, would have dropped out of school, the marginal student affected by the program could be different from other students. For instance, if those induced to remain in high school have lower ability, our estimates on the ICFES score are likely to be a lower bound of the true impact.

[32]Results on the first stage are presented in Appendix Table A.6, which show that: (i) there is a strong relationship between eligibility and participation (Appendix Table A.6 shows that the first stage F-statistic is larger than 400); and (ii) being eligible for the CCT program increases participation by 30 p.p.

[33]Appendix Figure A.4 presents graphical RD figures for our outcomes.

5.2 The Interactive Effects Between Weather Shocks and CCTs on Human Capital

5.2.1 Average interactive effects

We now turn our attention to the main focus of our analysis, which is the interactive effects between weather shocks and CCTs, obtained by estimating equation (5). Columns 2 and 3 in Tables 4 and 5 display these results. To facilitate interpretation of our estimates, we show effect sizes in the bottom part of the tables for three types of children: those who were only exposed to the CCT program, those who were only exposed to 8 months of adverse weather conditions in early life, and those who were exposed to both shocks.[34]

Our findings show imprecise estimates on the differential impact of the CCT program on children exposed to weather shocks. Across the two outcomes, we observe that the coefficients on the interaction are not statistically significant and the signs of the coefficients change from negative (continued enrollment) to positive (end-of-high school exam). While the point estimate of the interaction for continued enrollment is moderately small (-0.0018 per month or -2.5% w.r.t. the outcome mean), we can rule out interactive effects below -7.5% or above 2.4% for this outcome, at the weather shock exposure of 8 months. Similarly, given the small coefficient on the interaction for the Icfes score (0.006 SD), we can rule out interactive effects below -0.12 SDs and above 0.13 SDs.[35]

Despite the moderately small and imprecise effect on the interaction, we find that for children who were exposed to adverse weather and who later received the CCT program, the average effect of the program is large enough to help undo the decline in education caused by

[34] To calculate the effect sizes that involve early-life weather shocks, we multiply the point estimates by 8 months, as explained in Section 5.1. Whereas the effect of the CCT program on the outcome is given by the point estimate, effect sizes (weather, CCT, and the interaction) are expressed as % of the outcome mean (for continued enrollment) or SD (for the end-of-high-school exam score).

[35] For the ICFES exam analysis, a potential selection concern can arise as the CCT, the weather shock, and their interaction can affect who takes the exam. To address this, we estimate our main specification on a dummy variable for test-taking. Appendix Table A.7 shows that the CCT increases the outcome, which is unsurprising given that the CCT promotes school attendance and increases school completion for those who would otherwise drop out. Thus, the marginal student affected by the program could be different from other students (e.g., lower ability). Second, exposure to the weather shock decreases the probability of taking the exam, which could counteract the positive impact of the CCT. Third, the estimate of the interaction is small and statistically insignificant, which means that selection does not seem to be contaminating our estimates of the interaction for the ICFES exam.

these shocks. In that sense, CCTs help to partially close the gap between weather-affected and unaffected children. For example, in Table 4 (column 3), we observe that a child only exposed to extreme weather early in life experiences a decline in the probability of continued enrollment of 4.1%, while a weather-unaffected child who received the CCT program shows an increase in this probability by 11.9%. In contrast, a child exposed to both treatments experiences a net positive increase of 5.3%. Similarly, for the end-of-high school exam (Table 5), a child exclusively exposed to early-life weather shocks suffers a decline of 0.04 SDs in the score, while a weather-unaffected child who participates in the CCT experience an increase of 0.13 SDs. Conversely, a child exposed to both treatments perceives a net positive increase of 0.10 SDs.[36]

5.2.2 Heterogeneous interactive effects

Table 6 shows the heterogeneous effects by age at CCT rollout. We present estimates for children who were exposed to the program before and after age 7, which corresponds to the cutoff where the CCT-induced investments switch from health to education. As explained before, these estimates represent the effects of the bundle of type and timing (and possibly, duration) of CCT investments.

Columns 1 and 4 in Table 6 report the average effect of the CCT program for each subsample of children. Results indicate that those who received CCTs early experienced a much larger increase in the probability of continued enrollment than those who received it later. These effects are 12% (statistically significant) vs. 4% (not statistically significant), which indicates that the joint impact of type and timing (and duration) of investments matter for the effects the CCT program.[37] Columns 2 and 5 show that these effects remain unchanged when we control for weather shock exposure and that the coefficients on the weather variable are very similar across samples, suggesting that in utero to age 3 is a critical period of human capital development.

[36] We use an 8-month exposure period to scale our weather-shock coefficients, which corresponds to the median duration of the weather shock and also coincides with the change from the 25th to the 75th percentile in the weather-shock distribution. If we use a change from the 10th to the 90th percentile, our conclusions remain unchanged.

[37] Appendix Figure A.5 shows an age profile of the effects of the CCT on continued enrollment by child's age at rollout, which further corroborates that the estimated impacts of the CCT tend to be larger for children who received it at younger ages.

Columns 3 and 6 of Table 6 report the interactive effects between weather shocks and CCTs. Column 3 of Table 6 shows that for children who receive the CCT before age 7, the interactive effect with the weather shock is negative and statistically significant, which suggests that the CCT has a smaller net impact per additional month of adverse weather exposure. Scaling the coefficients by the 8-months of adverse weather duration shows that the interactive effect reduces the program's effectiveness by nearly one-third of its average treatment effect,[38] while still maintaining a positive impact. In contrast, Column 6 shows that for children who received the CCT later in childhood or in adolescence, the interactive effect is smaller in magnitude and not significant. And although we cannot reject the null hypothesis that the coefficients on the interaction across samples are statistically different, Table 6 shows that the interaction coefficient on older children is almost half the size of that for children who received it at younger ages (columns 6 vs. 3).

In sum, our results are consistent with the idea that when the CCT investment arrives late in childhood, both the main effect of the program and its interaction with early shocks have weaker impacts on continued enrollment compared to those observed when the the CCT arrives at younger ages.

Validating the role of timing on other educational outcomes Table 7 shows heterogeneous impacts on other educational outcomes observed for children exposed to the program at young vs. older ages. These outcomes are being “on time" for completing 7th, 8th, or 9th grade based on a child's age, which capture both educational attainment and achievement dimensions. Results show that children who were exposed to the program early in life experience both a larger effect of the CCT and a negative and significant interactive effect with the weather shock (Panel A), compared to those exposed later (Panel B), thus highlighting a similar pattern to that observed for continued enrollment.

How do our results relate to the theory on human capital formation? Our findings on the heterogeneous interactive effects are not only novel in the literature but they are consistent with leading theories on human capital formation. In Appendix Section E we lay

[38]This estimate is obtained by multiplying the coefficient on the interaction by 8 months of extreme weather (-0.0062×8) divided by the coefficient on the main effect of the CCT (0.1418).

out a simple theoretical framework, which follows closely the work by Cunha and Heckman (2007), in order to discuss our reduced-form estimates in light of key theoretical predictions of the model.

6 Sources of Selection Bias and Robustness Checks

In this section, we analyze whether the effects of weather shocks or CCTs induce potential sources of bias, including mobility, fertility, or mortality (as discussed in Almond, 2006; Bozzoli et al., 2009). Additionally, we present several robustness checks that validate our empirical strategy.

6.1 Mobility

Families that experience weather shocks when their children are young may be more likely than other families to migrate from their municipality of residence, and if migrant families differ from those who stay in terms of their characteristics, this could bias the effects of weather shocks on children's outcomes.

We define migrant children as those whose municipality of birth differs from their municipality of residence at SISBEN-interview, which we find to be 30% of the sample.[39] To test for selective mobility, we analyze whether families whose children were exposed to shocks were more or less likely to move over time, and if so, whether this differed by household's characteristics. The associations presented in Appendix Table C.1 show little evidence that families move in response to the shocks; however, we do find some differential responses across families. For instance, those in which the parents are married are 2.4% more likely to migrate in response to the weather shock exposure. Despite these differential responses across some groups, endogenous mobility does not pose a significant threat to our analysis because (i) the magnitudes of these associations are small and (ii), assigning shock-exposure based on a child's municipality of birth (rather than municipality of residence) provides an

[39] Descriptive evidence from the population Census of 2005 indicates that the main cause for migration is due to family reasons, 54%; whereas migration due to natural disasters only represents 2.9% of migrants. International migration does not pose a significant threat to our analysis given that this is uncommon among low-income households in this context.

arguably exogenous “treatment."

Regarding migration responses due to CCTs, Appendix Table C.2 shows negligible effects across most groups except for large families who are 0.6% less likely to change municipality in response to the program. Given the small magnitude of this effect, it is unlikely that migration is driving the effects of CCTs on children.

6.2 Fertility

First, we examine the relationship between weather shocks and fertility using data from the population Census of 2005 and several waves of DHS data. In Appendix Table C.3 we report estimates on the relationship between contemporaneous, lagged, and lead realizations of the shock and fertility as measured by the cohort size (total population born by cohort), sex ratio (number of males vs. females in a given cohort), child's gender, and by characteristics of women giving birth. We find little evidence that the weather shock is associated with changes in these outcomes. In fact, most of the coefficients are small and statistically insignificant. We then examine fertility responses within families with children born in our cohorts of interest, to analyze subsequent fertility plausibly triggered by the shock. Results shown in Appendix Table C.4 suggest little evidence of endogenous fertility responses as measured by total fertility after a focal child and birth spacing between subsequent siblings.

Second, we analyze the effects of the CCT on fertility. Column (1) in Appendix Table C.5 indicates that being eligible for the program is associated with an increase in total fertility (after the focal child) of 0.044 children (with an outcome mean of 0.78 children), which seems to be driven by married mothers (who experience an increase of 0.045 in the outcome). Previous research has shown that CCTs can have unintended effects on fertility. Stecklov et al. (2007) showed that the Hondurian CCT program raised fertility by 4 p.p. among married mothers. One possible way to account for this selective response in our model, is to control for marital status (which we do).

6.3 Mortality

The estimates of early-life shocks may also be affected by selective mortality both at birth and during early childhood, and if those in weaker health are more likely to die, then, our impacts would likely represent lower bound estimates of the true effect. To test this hypothesis, we use several waves of DHS data. As outcomes, we focus on the probability that a child dies in the first month of life, before age 1, and before age 3. Appendix Table C.6 shows that the weather shock is not associated with changes in child mortality.[40]

6.4 Additional Robustness Checks

Online Appendix D presents several robustness checks. First, we show that our results are robust to different specifications of both the weather shock and the CCT such as: i) separating the effect of floods vs. droughts and using alternative definitions of the weather shock (i.e., defining shocks using SDs units or using different percentile cutoffs) (Section D.1); and ii) using alternative definition of the CCT (i.e., defining participation in months of exposure to the program) (Section D.2). Second, we test the robustness of our results by: i) excluding the socio-demographic covariates, ii) adding municipality-specific linear-time trends, and iii), using different RD-bandwidths. Panels a)-f) in Appendix Figure D.1 show that our estimates are robust to these tests. Third, we examine if our estimates of early-life weather shocks could be driven by exposure at other ages such as before conception or after age 3. Appendix Tables D.3 and D.4 reveal that this does not seem to be the case. In fact, the coefficients on these “additional” shocks are small and statistically insignificant. Fourth, we analyze whether our results could be confounded with other co-occurring adverse shocks for human capital such as violence exposure as measured by homicide rates at the municipality-year level. Lastly, we explore the potential role of selective matching across datasets.

[40] We also examine how changes in weather conditions affect the cohort size and sex ratio—two key indicators of demographic change. We use 2005 Census data to construct these outcomes, since they provide information on the total population (SISBEN data only include information on the poorest households). Consistent with the finding that the weather shock has little effect on child mortality, results in Appendix Table C.7 show that rainfall shocks in early life do not seem to be associated with changes in neither of these outcomes.

7 Conclusions

This paper provides new evidence on the interaction between early-life endowments and subsequent human capital investments, by focusing on two policy-relevant shocks that affect millions of households across the world, adverse weather and conditional cash transfer programs. We combine a DD framework of exposure to weather shocks with an RD design of CCTs to examine if children who were born or lived through their early years in areas less affected by floods or droughts, and who later received the cash transfer, experience a larger return of the CCT program on their future educational outcomes relative to those affected by the shock.

We show that the joint impact of timing and type of CCT-induced investments matter for both the "main" effects of the program as well as its interactive effects with weather shocks. When these induced investments arrive early in childhood and include a health-specific component, the effects of the program are large but their interactive effects with weather shocks suggest that the net returns are lower for children exposed to adverse weather. In contrast, CCT-induced investments that come relatively late in childhood (e.g., adolescence) and include an education-only component, have a smaller "main" effect and a smaller interactive impact with the weather shock. Together, these findings shed new light on the process of child development, as they provide evidence that the interactions between different shocks to human capital depend on the characteristics of the investments (timing, type, duration of exposure).

Although our results show that children affected by whether shocks tend to experience a lower return of CCTs compared to weather unaffected children, we find that the positive effect of the program helps undo the damage caused by early-life shocks. In other words, weather-affected children tend to partially catch-up with their unaffected peers, if they participate in the program and especially if they do so at an early age, as the "main" effect of the CCT is strictly larger (and positive) than the negative effect of the weather shock.

Our results are policy relevant across several dimensions. First, weather shocks are becoming more prevalent and unpredictable in terms of intensities and durations (Climate Prediction Center, 2005), highlighting the importance of policies that help mitigate adverse effects (Zebiak et al., 2015). Second, developing countries are disproportionately affected by weather shocks relative to other countries, in part because, their economic activity is more dependent on agriculture and because they have lower infrastructure, less-adequate health systems, weaker credit markets, and more limited safety net programs (Dell et al., 2014). Third, children in these contexts may be the group most at risk from extreme weather conditions. Children are not only more physically vulnerable than adults, but they are less able to protect themselves under extreme weather conditions (Bharadwaj and Vogl, 2016; Hanna and Oliva, 2016). Fourth, CCT programs have become a popular mechanism for alleviating poverty. Today, more than 60 low- and middle-income countries (including the U.S. and the U.K.) operate a CCT and their costs represent a large component of the social safety net. Therefore, learning about their potential direct and indirect impacts is imperative. Lastly, the results of this paper highlight the importance of intervening early in children's lives to maximize program effectiveness and reduce initial gaps across groups.

References

Adhvaryu, A., T. Molina, A. Nyshadham, and J. Tamayo (2019). Helping children catch up: Early life shocks and the progresa experiment. Technical report, University of Michigan.

Aguilar, A. and M. Vicarelli (2012). El Niño and Mexican children: Medium-term effects of early-life weather shocks on cognitive and health outcomes. Technical report, Yale Climate and Energy Institute, Yale University. Job Market Paper.

Aiyagari, S. R., J. Greenwood, and A. Seshadri (2002). Efficient investment in children. *Journal of economic theory 102*(2), 290–321.

Akresh, R. (2016). Climate change, conflict, and children. *The Future of Children 26*(1), 51–71.

Akresh, R., E. Bagby, D. de Walque, and H. Kazianga (2012). Child labor, schooling, and child ability. Technical report, World Bank.

Akresh, R., S. Bhalotra, M. Leone, and U. Osili (2021). First and second generation impacts of the biafran war. *Journal of Human Resources*, 0118–9272R1.

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

Almond, D., J. Currie, and V. Duque (2017). Childhood circumstances and adult outcomes: Act II. Technical report, National Bureau of Economic Research.

Almond, D. and B. Mazumder (2013). Fetal origins and parental responses. *Annual Review of Economics 5*(1), 37–56.

Attanasio, O., E. Fitzsimons, A. Gomez, M. I. Gutierrez, C. Meghir, and A. Mesnard (2010). Children's schooling and work in the presence of a conditional cash transfer program in rural Colombia. *Economic development and cultural change 58*(2), 181–210.

Attanasio, O., C. Meghir, and M. Vera-Hernandez (2004). Baseline report on the evaluation of Familias en Acción. Technical report, Institute for Fiscal Studies.

Baez, J. E. and A. Camacho (2011). Assessing the long-term effects of conditional cash transfers on human capital: Evidence from Colombia. Technical report, World Bank. Policy Research Working Paper Series.

Baez, J. E., A. de la Fuente, and I. Santos (2010). Do natural disasters affect human capital? An assessment based on existing empirical evidence. Technical report, Institute for the Study of Labor (IZA).

Baird, S., F. H. G. Ferreira, B. Özler, and M. Woolcock (2014). Conditional, unconditional and everything in between: A systematic review of the effects of cash transfer programmes on schooling outcomes. *Journal of Development Effectiveness 6*(1), 1–43.

Barham, T., K. Macours, and J. A. Maluccio (2018). More schooling and more learning? Effects of a three-year conditional cash transfer program in Nicaragua after 10 years. Technical report, CEPR. Discussion Paper 11937.

Barker, D. J. (1990). The fetal and infant origins of adult disease. *BMJ: British Medical Journal 301*(6761), 1111.

Becker, G. S. and N. Tomes (1986). Human capital and the rise and fall of families. *Journal of labor economics 4*(3, Part 2), S1–S39.

Berthelon, M., D. Kruger, and R. Sanchez (2021). Maternal stress during pregnancy and early childhood development. *Economics & Human Biology 43*, 101047.

Bharadwaj, P. and T. S. Vogl (2016). Crisis and human biology. *The Oxford Handbook of Economics and Human Biology*, 52.

Bleakley, H. (2007). Disease and development: Evidence from hookworm eradication in the American south. *Quarterly Journal of Economics 122*(1), 73–117.

Bleakley, H. (2010). Health, human capital, and development. *Annu. Rev. Econ. 2*(1), 283–310.

Borghans, L., B. H. Golsteyn, J. J. Heckman, and J. E. Humphries (2016). What grades and achievement tests measure. *Proceedings of the National Academy of Sciences 113*(47), 13354–13359.

Borghans, L. and T. Schils (2018). Decomposing achievement test scores into measures of cognitive and noncognitive skills. *Available at SSRN 3414156*.

Bozzoli, C., A. Deaton, and C. Quintana-Domeque (2009). Adult height and childhood disease. *Demography 46*(4), 647–669.

Brando, J. and R. J. Santos (2015). La niña y los niños: Effects of an unexpected winter on early life human capital and family responses. *Documento CEDE* (2015-25).

Brunner, A. D. (2002). El niño and world primary commodity prices: Warm water or hot air? *Review of Economics and Statistics 84*(1), 176–183.

Cahyadi, N., R. Hanna, B. A. Olken, R. A. Prima, E. Satriawan, and E. Syamsulhakim (2018). Cumulative impacts of conditional cash transfer programs: Experimental evidence from indonesia. *National Bureau of Economic Research*.

Calonico, S., M. D. Cattaneo, R. Titiunik, et al. (2014). Robust data-driven inference in the regression-discontinuity design. *Stata Journal 14*(4), 909–946.

Camacho, A. (2008). Stress and birth weight: evidence from terrorist attacks. *American Economic Review 98*(2), 511–515.

Camacho, A. and E. Conover (2011). Manipulation of social program eligibility. *American Economic Journal: Economic Policy 3*(2), 41–65.

Climate Prediction Center (2005). Frequently asked questions about El Niño and La Niña. Technical report, National Centers for Environmental Prediction.

Cunha, F. and J. Heckman (2007). The technology of skill formation. *American Economic Review 97*(2), 31–47.

Cunha, F., J. J. Heckman, and S. M. Schennach (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica 78*(3), 883–931.

Currie, J. (2009). Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. *Journal of economic literature 47*(1), 87–122.

Currie, J. and T. Vogl (2013). Early-life health and adult circumstance in developing countries. *Annual Review of Economics 5*, 1–36.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? The new climate–economy literature. *Journal of Economic Literature 52*(3), 740–798.

Departamento Administrativo Para la Prosperidad Social (2017). Modificaciones al presupuesto desagregado vigencia, 2017: Mes de agosto. Technical report, Departamento Administrativo Para la Prosperidad Social. http://www.dps.gov.co/ent/ifc/Documentos%20compartidos/Presupuesto-Desagregado-Modificaciones-Agosto-2017.pdf.

Departamento Nacional De Planeación (2005). Aprendizaje colectivo: Familias en Acción. Technical report, DNP.

Dinkelman, T. (2017). Long-run health repercussions of drought shocks: Evidence from South African homelands. *Economic Journal 127*(604), 1906–1939.

Duque, V. (2017). Violence and children's education: Evidence from administrative data. Technical report, Working paper.

Fay, M., S. Hallegatte, M. Bangalore, T. Kane, J. Rozenberg, A. Vogt-Schilb, U. Narloch, L. Bonzanigo, and D. Treguer (2015). *Shock Waves: Managing the Impacts of Climate Change on Poverty*. Washington, DC: World Bank.

Fiszbein, A. and N. Schady (2009). Conditional cash transfers: A World Bank policy research report. Technical report, World Bank. Policy Research Report.

Frandsen, B. R. (2016). Party bias in union representation elections: Testing for manipulation in the regression discontinuity design when the running variable is discrete. Technical report, Department of Economics, Brigham Young University. Unpublished manuscript.

García, S. and J. Hill (2010). Impact of conditional cash transfers on children's school achievement: Evidence from Colombia. *Journal of Development Effectiveness 2*(1), 117–137.

García, S. and J. E. Saavedra (2017). Educational impacts and cost-effectiveness of conditional cash transfer programs in developing countries: A meta-analysis. *Review of Educational Research 87*(5), 921–965.

Gilraine, M. (2017). School accountability and the dynamics of human capital formation.

Gluckman, P. and M. Hanson (2005). *The Fetal Matrix: Evolution, Development and Disease*. Cambridge, England: Cambridge University Press.

Goff, L., O. Malamud, C. Pop-Eleches, and M. Urquiola (2023). Interactions between family and school environments: Access to abortion and selective schools. *Journal of Human Resources*.

Guerreiro, M. J., T. Lajinha, and I. Abreu (2008). Flood analysis with the standardized precipitation index (SPI). *Revista da Faculdade de Ciência e Tecnologia 2007*(4), 8–14.

Gunnsteinsson, S., A. Adhvaryu, P. Christian, A. Labrique, J. Sugimoto, A. A. Shamim, and K. P. West Jr. (2014). Resilience to early life shocks. Technical report, National Bureau of Economic Research.

Hanna, R. and P. Oliva (2016). Implications of climate change for children in developing countries. *Future of Children 26*, 115–132.

Heckman, J. J. (2008). Schools, skills, and synapses. *Economic inquiry 46*(3), 289–324.

Hsiang, S. M. and A. S. Jina (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Technical report, National Bureau of Economic Research.

Imbens, G. and K. Kalyanaraman (2012). Optimal bandwidth choice for the regression discontinuity estimator. *Review of Economic Studies 79*(3), 933–959.

Instituto de Hidrología, Meteorología y Estudios Ambientales (2002). Efectos naturales y socioeconómicos del fenómeno El Niño en Colombia. Technical report, Instituto de Hidrología, Meteorología y Estudios Ambientales.

International Federation of Red Cross and Red Crescent Societies (2000). Colombia: Floods. Technical report, International Federation of Red Cross and Red Crescent Societies. Information Bulletin 3.

Johnson, R. C. and C. K. Jackson (2019). Reducing inequality through dynamic complementarity: Evidence from head start and public school spending. *American Economic Journal: Economic Policy 11*(4), 310–49.

Knudsen, E. I., J. J. Heckman, J. L. Cameron, and J. P. Shonkoff (2006). Economic, neurobiological, and behavioral perspectives on building America's future workforce. *Proceedings of the National Academy of Sciences 103*(27), 10155–10162.

Kovats, R. S., M. J. Bouma, S. Hajat, E. Worrall, and A. Haines (2003). El Niño and health. *Lancet 362*(9394), 1481–1489.

Lee, D. S. and T. Lemieux (2010). Regression discontinuity designs in economics. *Journal of Economic Literature 48*(2), 281–355.

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

Malamud, O., C. Pop-Eleches, and M. S. Urquiola (2016). Interactions between family and school environments: Evidence on dynamic complementarities? Technical report, National Bureau of Economic Research. Working Paper w22112.

Mogstad, M. (2017). The human capital approach to intergenerational mobility. *Journal of Political Economy 125*(6), 1862–1868.

Molina-Millan, T., T. Barham, K. Macours, J. A. Maluccio, and M. Stampini (2016). Long-term impacts of conditional cash transfers in Latin America: Review of the evidence. Technical report, Inter-American Development Bank.

Parker, S. W. and T. S. Vogl (2021). Do conditional cash transfers improve economic outcomes in the next generation? evidence from mexico.

Rocha, R. and R. R. Soares (2015). Water scarcity and birth outcomes in the Brazilian semiarid. *Journal of Development Economics 112*, 72–91.

Rojas, O., L. Yanyun, and R. Cumani (2014). *Understanding the Drought Impact of El Niño on the Global Agricultural Areas: An Assessment Using FAO's Agricultural Stress Index (ASI).* Rome, Italy: Food and Agriculture Organization of the United Nations.

Rosales-Rueda, M. (2018). The impact of early life shocks on human capital formation: Evidence from el niño floods in ecuador. *Journal of health economics 62*, 13–44.

Rossin-Slater, M. and M. Wust (2020). What is the added value of preschool for poor children? long-term and intergenerational impacts and interactions with an infant health intervention. *American Economic Journal: Applied Economics 12*(3), 255–86.

Sanson, A. V., J. Van Hoorn, and S. E. Burke (2019). Responding to the impacts of the climate crisis on children and youth. *Child Development Perspectives*.

Seiler, R. A., M. Hayes, and L. Bressan (2002). Using the standardized precipitation index for flood risk monitoring. *International Journal of Climatology 22*(11), 1365–1376.

Shah, M. and B. M. Steinberg (2017). Drought of opportunities: Contemporaneous and long term impacts of rainfall shocks on human capital. *Journal of Political Economy 125*, 527–561.

Stecklov, G., P. Winters, J. Todd, and F. Regalia (2007). Unintended effects of poverty programmes on childbearing in less developed countries: experimental evidence from latin america. *Population Studies 61*(2), 125–140.

Sviatschi, M. M. (2018). Making a narco: Childhood exposure to illegal labor markets and criminal life paths. Technical report, Princeton University.

Thompson, R. A. and C. A. Nelson (2001). Developmental science and the media: Early brain development. *American Psychologist 56*(1), 5.

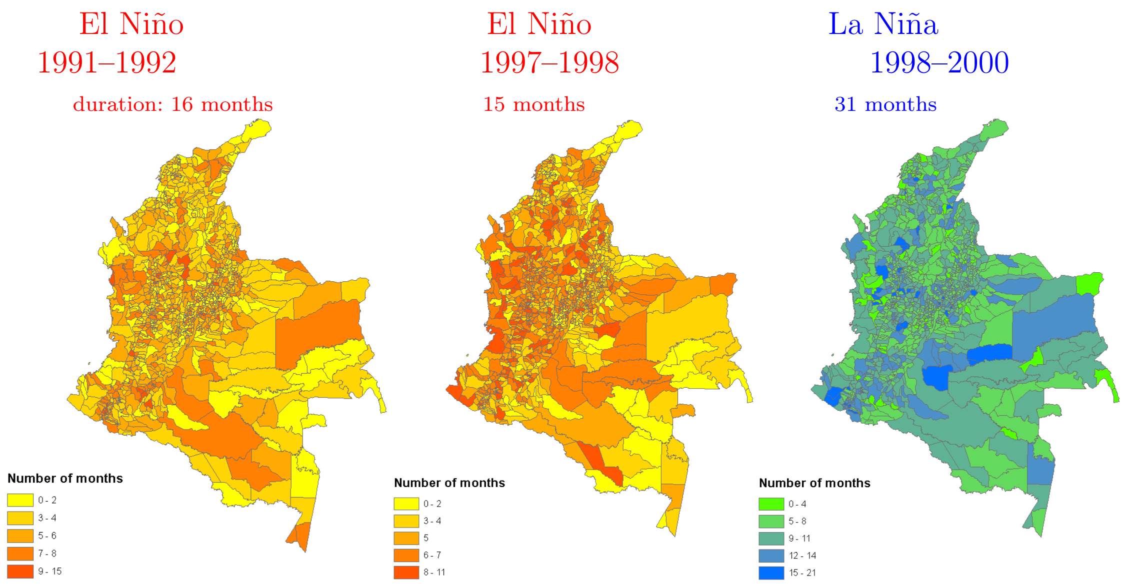
Trenberth, K. E., J. M. Caron, D. P. Stepaniak, and S. Worley (2002). Evolution of El Niño–southern oscillation and global atmospheric surface temperatures. *Journal of Geophysical Research: Atmospheres 107*(D8), AAC 5–1–AAC 5–17.

Wittenberg, A. T., A. Rosati, T. L. Delworth, G. A. Vecchi, and F. Zeng (2014). ENSO modulation: Is it decadally predictable? *Journal of Climate 27*(7), 2667–2681.

Zebiak, S. E., B. Orlove, Á. G. Muñoz, C. Vaughan, J. Hansen, T. Troy, M. C. Thomson, A. Lustig, and S. Garvin (2015). Investigating El Niño-southern oscillation and society relationships. *Wiley Interdisciplinary Reviews: Climate Change 6*(1), 17–34.

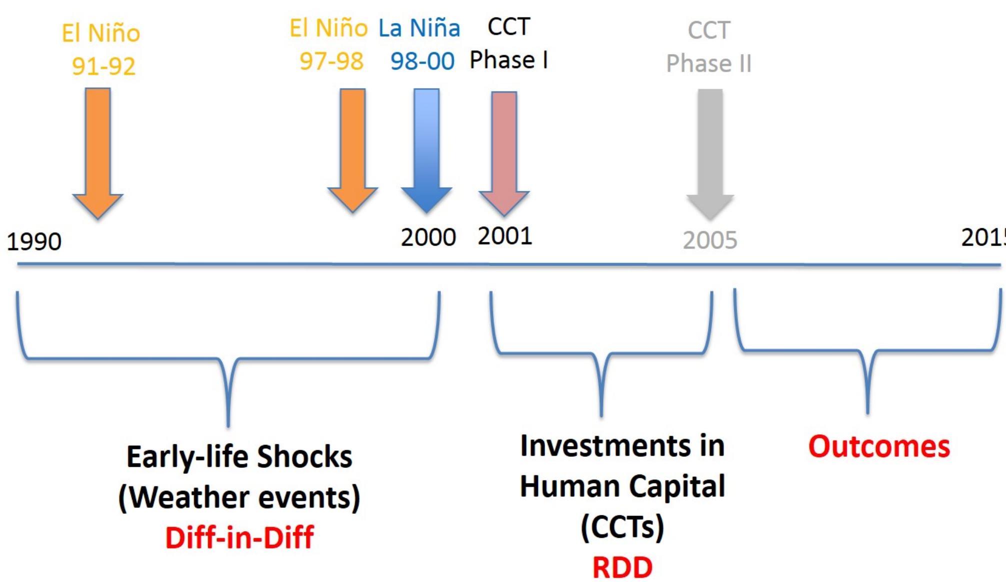
8 Figures and Tables

Figure 1: El Niño and La Niña Weather Shocks of the 1990s



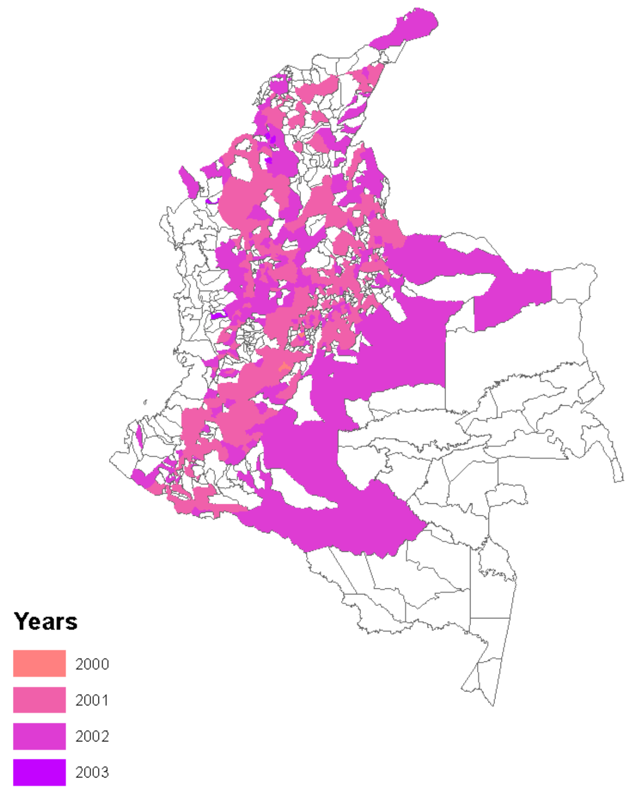
Note: The maps show the geographic variation in exposure to weather shocks during the climate events of interest. Each specific region corresponds to a municipality. The map displays the intensity of each shock measured as the number of months in which a municipality's monthly precipitation level during the windows of *El Niño* and *La Niña* events was above the 80th percentile or below the 20th percentile of the historical distribution in that municipality and month. Source: Rainfall dataset from the Colombian Institute of Meteorology and Environmental Studies, IDEAM.

Figure 2: Research Design



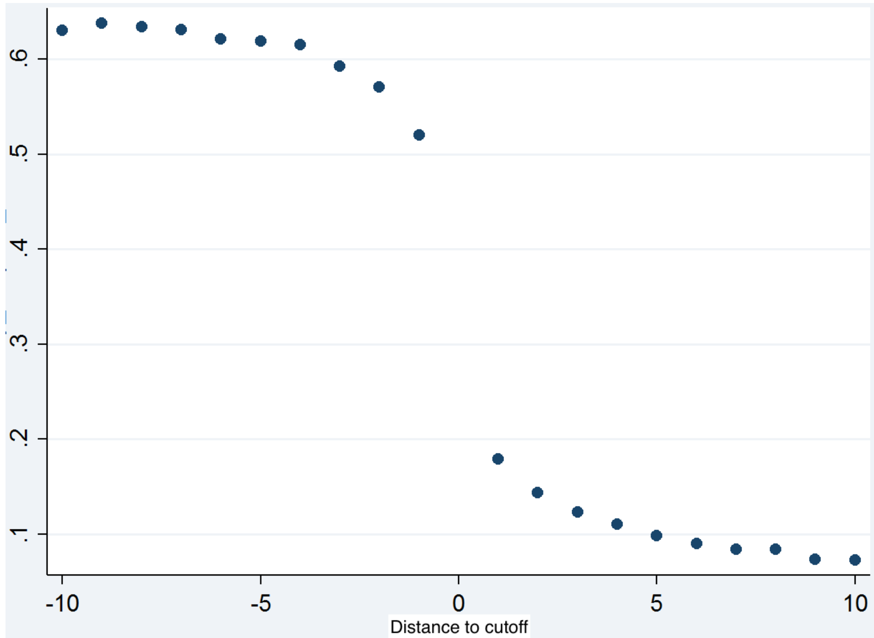
Note: The figure shows the chronological timing of the weather shocks during the 1990s and the introduction and later expansion of *Familias en Acción* in the 2000s (in this paper we only focus on the initial phase of *Familias en Acción*). The outcomes of interest are measured from 2005 and up to 2015.

Figure 3: Rollout of *Familias en Acción*—Phase I



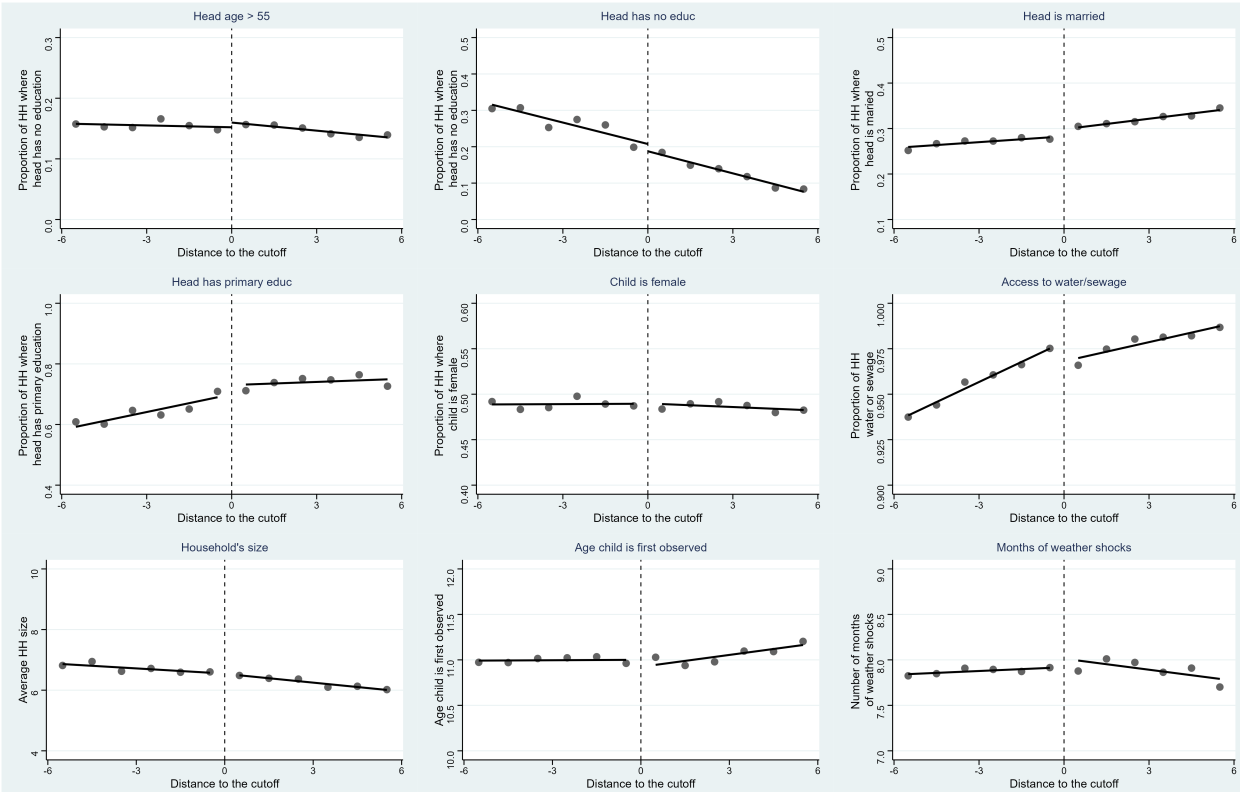
Note: The figure shows the municipalities covered by *Familias en Acción* by calendar year during phase I. Source: Ministry of Social Protection, Colombia.

Figure 4: Participation in *Familias en Acción*, Phase I



Note: The sample includes families in the urban segment of CCT municipalities in SISBEN Levels 1 and 2, around the cutoff for *Familias en Acción* eligibility. Each dot in the figure represents the average participation rate at each bin of one SISBEN score point. The SISBEN score is discrete and varies from 1 to 100. Thus, for instance, families located in the bin=-10 have a SISBEN score of 26 (10 points below the *Familias en Acción* cutoff of 36 in urban areas).

Figure 5: Sociodemographic Characteristics Around the Cutoff for *Familias en Acción*



Note: The sample includes families in the urban segment of CCT municipalities in SISBEN Levels 1 and 2 around the cutoff.

Table 1: Association between Early-life Weather and Household Characteristics

	Child is female	Child's age when first observed	Child's age when CCT arrived	Head is young (age<30)	Head is female
	(1)	(2)	(3)	(4)	(5)
Weather Shock Utero to Age 3	0.0017*	0.0032	-0.0038	-0.0004	-0.000
	[0.0009]	[0.0028]	[0.0048]	[0.0010]	[0.0010]
N	68,884	68,884	68,884	68,884	68,884

(continued...)

	Head has no education	Head has primary educ	Head is married	Has access to water or sewage	Household size
	(6)	(7)	(8)	(9)	(10)
Weather Shock Utero to Age 3	0.0004	0.0008	-0.0003	-0.000	0.0054
	[0.0008]	[0.0009]	[0.0008]	[0.0003]	[0.0066]
N	68,884	68,884	68,884	68,884	68,884

Note: The sample includes children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN score cutoff). Models include municipality, month, and year of birth FE; standard errors are clustered at the municipality level. The Weather Shock variable is measured as the number of months child was exposed to extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation distribution) during the events of interest (i.e., *El Niño* and *La Niña* shocks of the 1990s) from in utero to age 3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2: Association Between Early-life Weather Shocks and CCT Eligibility

	Eligible for CCT	Distance to cutoff eligibility	CCT Take-up
	(1)	(2)	(3)
Weather Shock Utero to Age 3	0.0010	-0.0044	-0.0001
	[0.0010]	[0.0034]	[0.0008]
N	68,884	68,884	68,884

Note: The sample includes children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN cutoff score). Models include municipality, month, and year of birth FE; standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3: Effects of Early-life Weather Shocks on Children's Education

	Continued enrollment		ICFES Exam (SD)	
	(1)	(2)	(3)	(4)
Weather Shock	-0.0038***	-0.0035***	-0.0055***	-0.0057*
Utero to Age 3	[0.0007]	[0.0011]	[0.0016]	[0.0033]
N	259,347	68,884	102,987	27,275
Sample	Full	RD	Full	RD
Mean	0.57	0.57	0	0
Effect size	-5.3%	-5.0%	-0.04 SD	-0.05 SD

Note: The sample includes children in the urban segment of CCT municipalities. The "Full" sample refers to all children of families in SISBEN Level 1 (eligible for the program) and SISBEN Level 2 (ineligible). The "RD" sample refers to children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN score cutoff). Models include municipality, month, and year of birth FE; standard errors are clustered at the municipality level. Control covariates include child's gender, age, and baseline school grade in dummies, household head education, age, family size, marital status, access to water/sewer system, and year of SISBEN interview dummies. The Weather Shock variable is measured as the number of months a child was exposed to extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation distribution) during the events of interest (i.e., *El Niño* and *La Niña* shocks of the 1990s) from in utero to age 3. Effect sizes are calculated using 8 months of exposure, which corresponds to the variation from the 25th percentile to the 75th. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Interaction between Early-life Weather Shocks and CCTs on Continued Enrollment

	Continued Enrollment		
	(1)	(2)	(3)
CCT	0.0538*	0.0536*	0.0681**
	[0.0289]	[0.0288]	[0.0322]
Weather Shock Utero to Age 3		-0.0035***	-0.0029**
		[0.0011]	[0.0011]
CCT * Weather Shock Utero to Age 3			-0.0018
			[0.0018]
N	68,884	68,884	68,884
Mean	0.57	0.57	0.57
Effect (CCT=Yes, Weather Shock=No)	9.5%	9.4%	11.9%
Effect (CCT=No, Weather Shock=Yes)		-4.9%	-4.1%
Effect (CCT=Yes, Weather Shock=Yes)	9.5%	4.5%	5.3%

Note: The sample includes children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN score cutoff). Models include municipality, month, and year of birth FE; standard errors are clustered at the municipality level. Control covariates include child's gender, age, and baseline school grade in dummies, household head education, age, family size, marital status, access to water/sewer system, and year of SISBEN interview dummies. The Weather Shock variable is measured as the number of months a child was exposed to extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation distribution) during the events of interest (i.e., *El Niño* and *La Niña* shocks of the 1990s) from in utero to age 3. The CCT variable refers to whether a child received the CCT investment; this variable is instrumented using eligibility for the program based on the SISBEN score. Column 1 and 2 instrument CCT participation using eligibility as instrument. Column 3 instruments CCT participation and its interaction with the weather shock using both eligibility and the weather shock interacted with eligibility as instruments (see Section 4 for details). The bottom of the table shows the implied effect size for three types of children: (i) children who were only exposed to the CCT (and not exposed to the weather shocks); (ii) children who were only exposed to the weather shocks (and not exposed to the CCT); and children who were exposed to both the CCT and the weather shocks. To calculate effect sizes that involve early-life weather shocks, we multiply the point estimates by 8 months (the variation from the 25th percentile to the 75th), whereas the effect of the CCT on the outcome is given by the point estimate. All effect sizes (weather, CCT and the interaction) are expressed as % of the outcome mean (or SD for the ICFES score). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Interaction between Early-life Weather Shocks and CCTs on the ICFES Exam

	ICFES Exam (SD)		
	(1)	(2)	(3)
CCT	0.1276*	0.1276**	0.1242
	[0.0750]	[0.0750]	[0.0813]
Weather Shock Utero to Age 3		-0.0053	-0.0055
		[0.0033]	[0.0041]
CCT * Weather Shock Utero to Age 3			0.0008
			[0.0083]
N	27,275	27,275	27,275
Mean	0	0	0
Effect (CCT=Yes, Weather Shock=No)	0.13SD	0.13SD	0.13SD
Effect (CCT=No, Weather Shock=Yes)		-0.04SD	-0.04SD
Effect (CCT=Yes, Weather Shock=Yes)	0.13SD	0.09SD	0.10SD

Note: The sample includes children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN score cutoff). Models include municipality, month, and year of birth FE; standard errors are clustered at the municipality level. Control covariates include child's gender, age, and baseline school grade in dummies, household head education, age, family size, marital status, access to water/sewer system, and year of SISBEN interview dummies. The Weather Shock variable is measured as the number of months a child was exposed to extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation distribution) during the events of interest (i.e., *El Niño* and *La Niña* shocks of the 1990s) from in utero to age 3. The CCT variable refers to whether a child received the CCT investment; this variable is instrumented using eligibility for the program based on the SISBEN score. Column 1 and 2 instrument CCT participation using eligibility as instrument. Column 3 instruments CCT participation and its interaction with the weather shock using both eligibility and the weather shock interacted with eligibility as instruments (see Section 4 for details). The bottom of the table shows the implied effect size for three types of children: (i) children who were only exposed to the CCT (and not exposed to the weather shocks); (ii) children who were only exposed to the weather shocks (and not exposed to the CCT); and children who were exposed to both the CCT and the weather shocks. To calculate effect sizes that involve early-life weather shocks, we multiply the point estimates by 8 months (the variation from the 25th percentile to the 75th), whereas the effect of the CCT on the outcome is given by the point estimate. All effect sizes (weather, CCT and the interaction) are expressed as % of the outcome mean (or SD for the ICFES score). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6: Interaction between Early-life Weather Shocks and CCTs on Continued Enrollment by Child's Age at CCT Rollout

	Continued enrollment					
	CCT rolled out<age 7			CCT rolled out>=age 7		
	(1)	(2)	(3)	(4)	(5)	(6)
CCT	0.0678*	0.0676*	0.1418**	0.0209	0.0203	0.0330
	[0.0394]	[0.0394]	[0.0578]	[0.0403]	[0.0402]	[0.0445]
Weather Shock		-0.0065***	-0.0046***		-0.0048***	-0.0036*
Utero to Age 3		[0.0014]	[0.0017]		[0.0015]	[0.0022]
CCT * Weather Shock			-0.0062**			-0.0035
Utero to Age 3			[0.0030]			[0.0045]
N	36,380	36,380	36,380	32,504	32,504	32,504
Mean	0.58	0.58	0.58	0.56	0.56	0.56
Effect:						
CCT=Yes, Weather Shock=No	11.7%	11.7%	24.4%	3.7%	3.6%	5.9%
CCT=No, Weather Shock=Yes		-9.0%	-6.3%		-6.9%	-5.1%
CCT=Yes, Weather Shock=Yes	11.7%	2.7%	9.5%	3.7%	-3.3%	-4.2%

Note: The sample includes children in the urban segment of the CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN cutoff score). Models include municipality, month, and year of birth FE; standard errors are clustered at the municipality level. Control covariates include child's gender and age dummies, maternal education, age, marital status, family size, access to water/sewer system, and year of SISBEN interview dummies. “CCT - rolled-out < age 7" refers to children who were age 7 or less when the CCT was rolled-out in their municipality, which implies that they were eligible to receive the health grant. “CCT - rolled-out > age 7" refers children who were 7 or older when the CCT was rolled-out in their municipality, which implies that they were only eligible to receive the education grant. The Weather Shock variable is measured as the number of months a child was exposed to extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality precipitation distribution) during the events of interest (i.e., *El Niño* and *La Niña* shocks of the 1990s) from in utero to age 3. The CCT variable refers to whether a child received the CCT investment. Column 1, 2, 4, and 5 instrument CCT participation using eligibility as instrument. Column 3 and 6 instrument CCT participation and its interaction with the weather shock using both eligibility and the weather shock interacted with eligibility as instruments (see Section 4 for details). The bottom of the table shows the implied effect size for three types of children: (i) children who were only exposed to the CCT (and not exposed to the weather shocks); (ii) children who were only exposed to the weather shocks (and not exposed to the CCT); and children who were exposed to both the CCT and the weather shocks. To calculate effect sizes that involve early-life weather shocks, we multiply the point estimates by 8 months (the variation from the 25th percentile to the 75th), whereas the effect of the CCT on the outcome is given by the point estimate. All effect sizes (weather, CCT, and the interaction) are expressed as % of the outcome mean (or SD for the ICFES score). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: Interaction between Early-life Weather Shocks and CCTs on Being “on Time” for Grade by Child’s Age at CCT Rollout

	Child is “on Time” for...					
	Grade 7		Grade 8		Grade 9	
Panel A : CCT rolled-out<age 7						
CCT	0.0487	0.1051**	0.0488	0.1071**	0.0399	0.0919*
	[0.0383]	[0.0526]	[0.0387]	[0.0532]	[0.0383]	[0.0524]
Weather Shock Utero to Age 3	-0.0038***	-0.0023	-0.0039***	-0.0024	-0.0032***	-0.0019
	[0.0012]	[0.0015]	[0.0012]	[0.0015]	[0.0012]	[0.0015]
CCT * Weather Shock Utero to Age 3		-0.0047*		-0.0049*		-0.0043
		[0.0028]		[0.0028]		[0.0028]
N	36,380	36,380	36,380	36,380	36,380	36,380
Panel B: CCT rolled-out>=age 7						
CCT	0.0212	0.0202	0.0198	0.0219	0.0189	0.0183
	[0.0262]	[0.0285]	[0.0262]	[0.0286]	[0.0261]	[0.0285]
Weather Shock Utero to Age 3	-0.0039***	-0.0040***	-0.0040***	-0.0038***	-0.0044***	-0.0045***
	[0.0008]	[0.0013]	[0.0008]	[0.0013]	[0.0008]	[0.0014]
CCT * Weather Shock Utero to Age 3		0.0003		-0.0006		0.0002
		[0.0030]		[0.0031]		[0.0031]
N	32,504	32,504	32,504	32,504	32,504	32,504

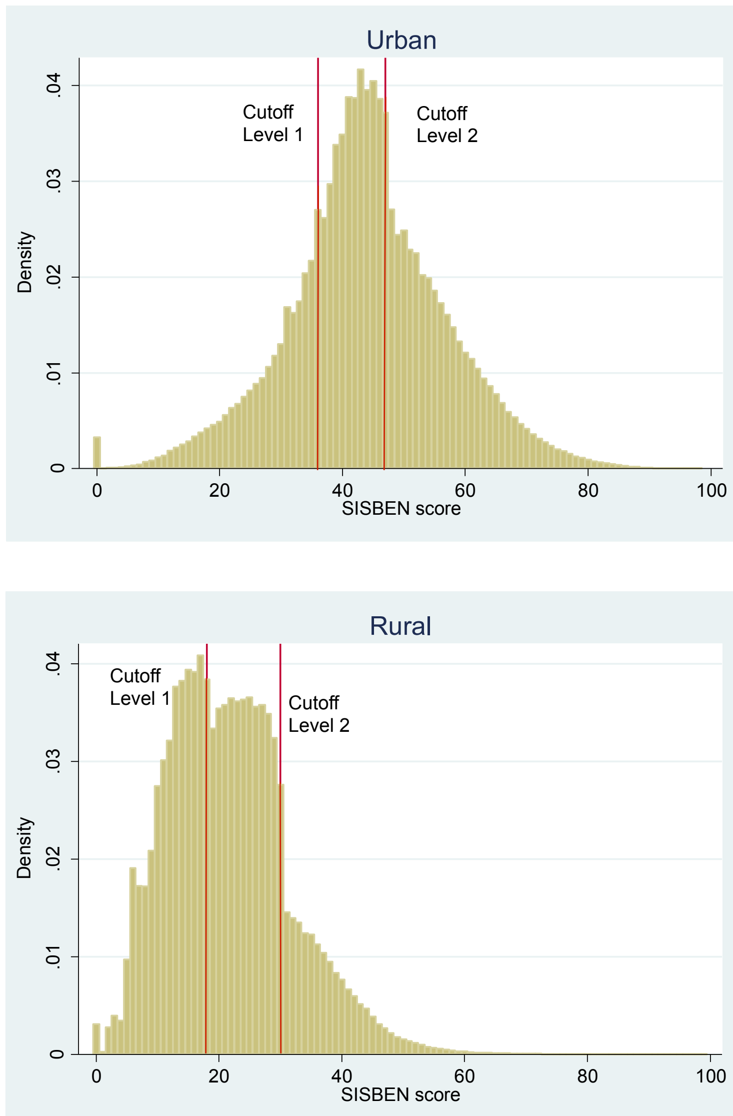
Note: The sample includes children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN cutoff score). The outcome being “on time" for grade is constructed as a dummy variable that compares a child’s age with the optimal age at a given school grade. We use as reference the fact that all children must be enrolled in primary school by age 7. Models include municipality, month, and year of birth FE; standard errors are clustered at the municipality level. Control covariates include child’s gender and age dummies, maternal education, age, marital status, family size, access to water/sewer system, and year of SISBEN interview dummies. “CCT - rolled out < age 7" refers to children who were age 7 or less when the CCT was rolled out in their municipality, which implies that they were eligible to receive the health grant. “CCT - rolled out > age 7" refers children who were 7 or older when the CCT was rolled out in their municipality, which implies that they were only eligible to receive the education grant. The Weather Shock variable is measured as the number of months a child was exposed to extreme weather (i.e., a municipality’s month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation distribution) during the events of interest (i.e., *El Niño* and *La Niña* shocks of the 1990s) from in utero to age 3. See Table 6 for further details. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

************** APPENDIX FOR ONLINE PUBLICATION **************

A Appendix: Additional Figures and Tables

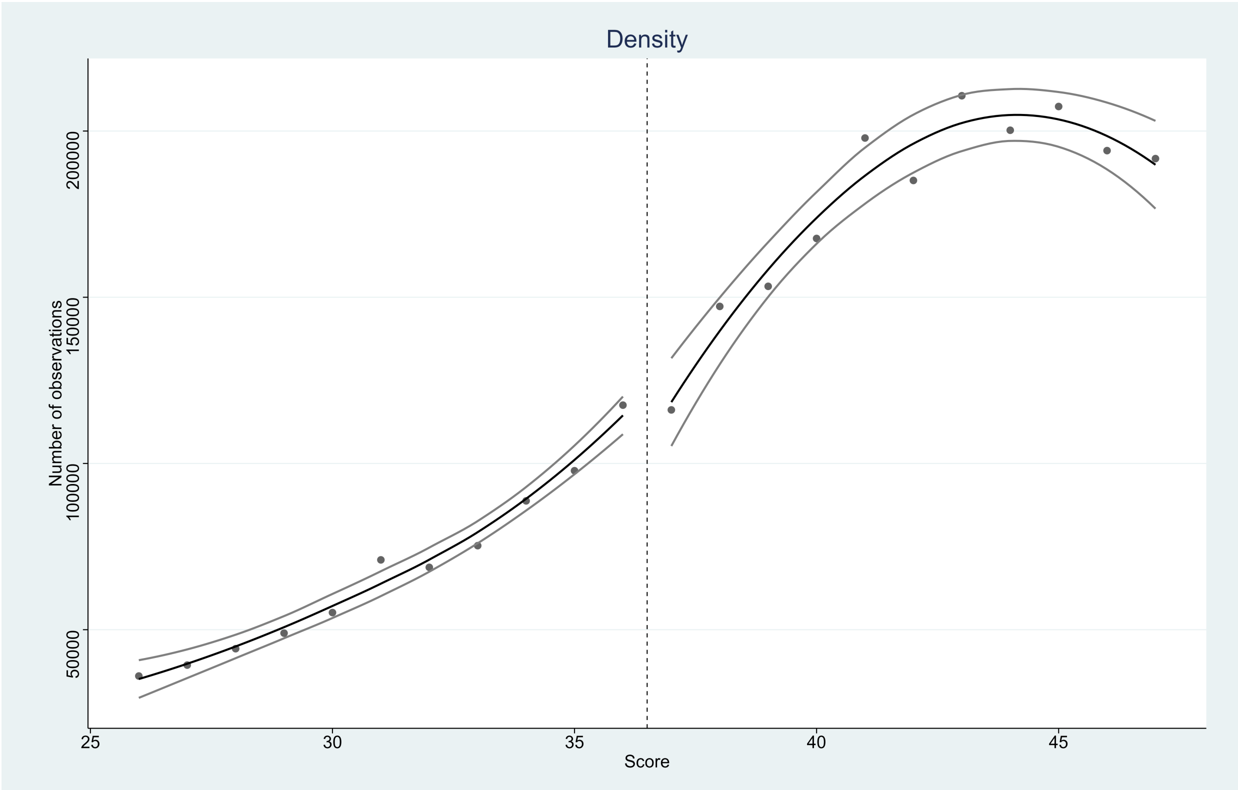
A.1 Figures

Figure A.1: Distribution of the SISBEN Score in Urban and Rural Areas



Note: The sample includes families across the whole SISBEN score distribution (Levels 1 through 6) in the "SISBEN I" (or Census of the poor) database. The cutoff between Levels 1 and 2 determines eligibility for the CCT, whereas the cutoff between Levels 2 and 3 determines eligibility for all other major social programs, such as subsidized health care or retirement pensions. The top figure shows the distribution of SISBEN scores in urban areas, and the bottom figure shows that for rural and remote areas.

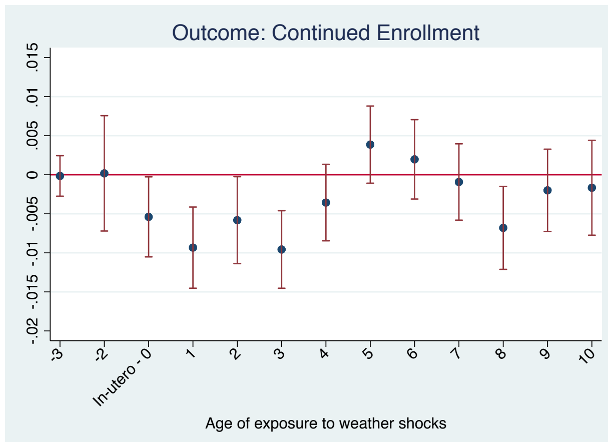
Figure A.2: Distribution of Running Variable Around the Threshold - Urban



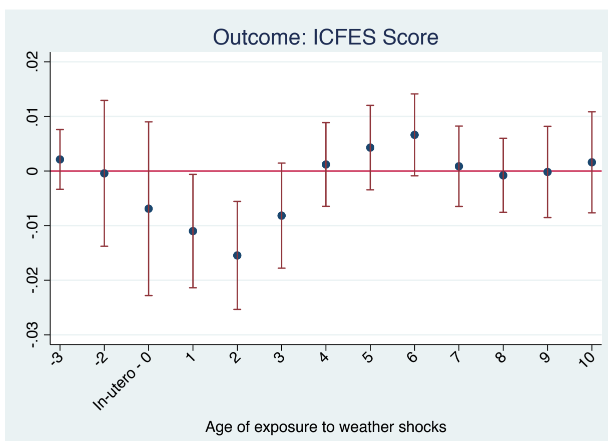
Note: The sample includes families around the SISBEN level 1 threshold in urban areas.

Figure A.3: Exposure to Weather Shocks by Child's Age

Panel A: Continued Enrollment



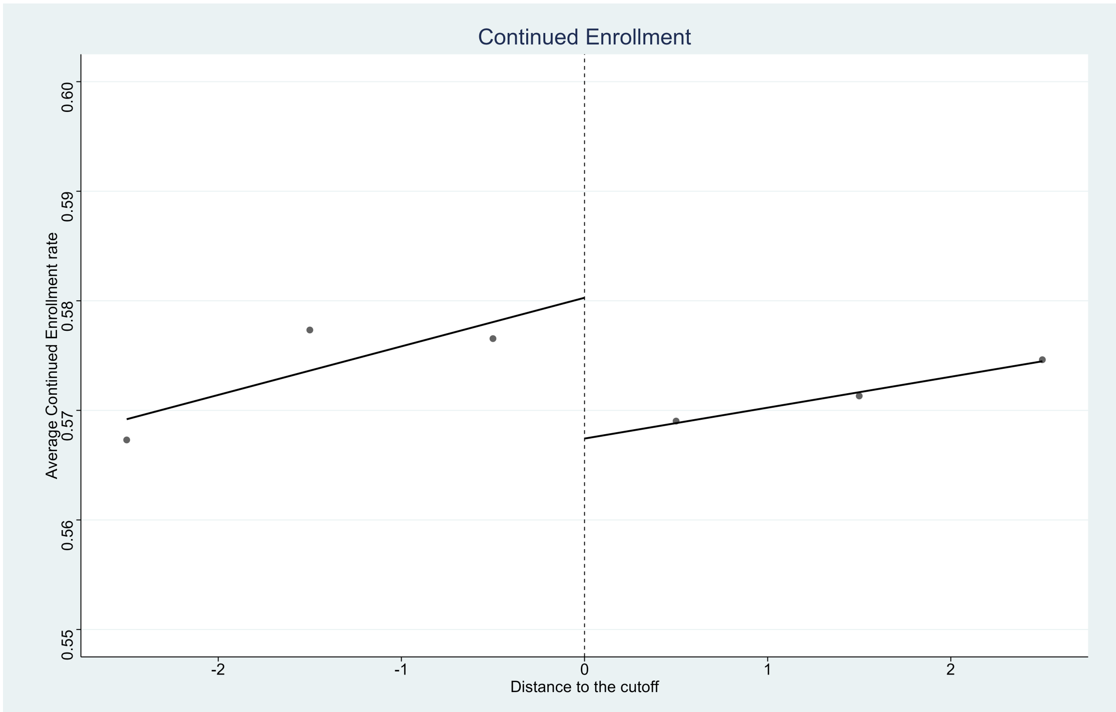
Panel B: End of High School ICFES Exam



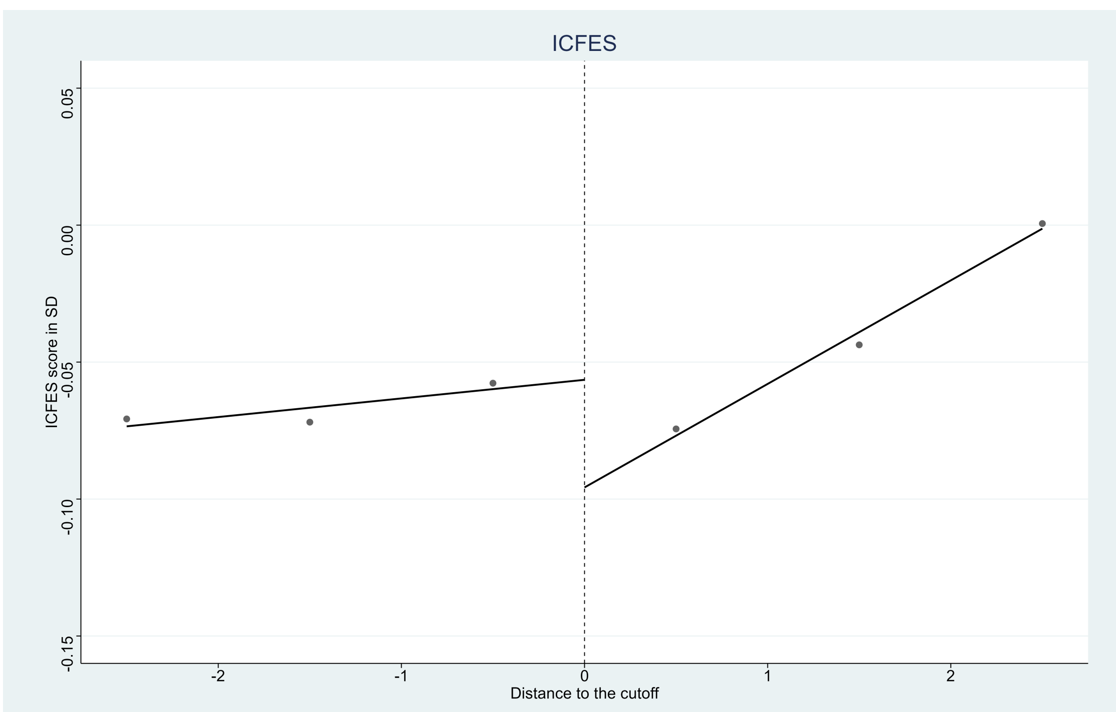
Note: Sample includes children in the urban segment of CCT municipalities. Figures display coefficients and confidence intervals from event study regressions that include as covariates municipality, month, and year of birth FE; errors are clustered at the municipality level. Control covariates include child's gender, age, and baseline school grade in dummies (for continued enrollment), household head education, age, family size, marital status, access to water/sewer system, and year of SISBEN interview dummies. The ICFES model also includes dummies for the age at which a child takes the exam and whether a child was enrolled in a school with morning versus other shifts. The Weather Shock variable is measured as the number of months a child was exposed to extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation distribution) during the events of interest (i.e., El Niño and La Niña shocks of the 1990s) from in utero to age 3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure A.4: Graphical RD figures

(a) Continued Enrollment

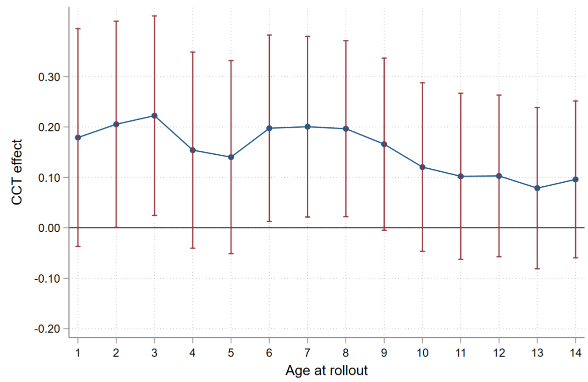


(b) ICFES Test Scores



Note: The sample includes families in the urban segment of CCT municipalities in SISBEN Levels 1 and 2 around the cutoff.

Figure A.5: CCT Effects - Age profile - Reduced form



Note: Sample includes children in the urban segment of CCT municipalities. Figures display coefficients and confidence intervals from computation of CCT effects by age at rollout using the reduced-form point estimates from the CCT and age at rollout dummies. Regression includes as covariates municipality, month, and year of birth FE; errors are clustered at the municipality level. Control covariates include child's gender, age, and baseline school grade in dummies (for continued enrollment), household head education, age, family size, marital status, access to water/sewer system, and year of SISBEN interview dummies. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.2 Additional Tables

Table A.1: Poverty Levels and SISBEN Score Cutoffs in Urban and Rural Areas

Level		Urban	Rural
1	(poorest; eligible for the CCT)	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

Note: This table shows the SISBEN score cutoffs used to determine eligibility for the program (i.e., Level 1). Note that thresholds vary by whether a household lives in a rural versus urban segment of the municipality. The CCT *Familias en Acción* is the only social program that exclusively targets Level 1, while other programs (e.g., subsidized healthcare) target Levels 1 and 2. Source: National Planning Department.

Table A.2: Summary Statistics

	Full sample (SISBEN levels 1 and 2)	RD sample (optimal bandwidth)
Household head characteristics		
Gender (female)	0.26	0.28
Age less than 32	0.31	0.31
Age 33–42	0.35	0.33
Age 43–54	0.20	0.20
No education	0.18	0.20
Primary	0.66	0.71
Married	0.30	0.29
Cohabiting	0.44	0.43
Has access to water or sewage	0.95	0.97
Household size	6.30	6.50
	[3.03]	[3.16]
SISBEN score	36.20	36.61
	[8.46]	[1.72]
Eligible to receive CCTs	0.44	0.49
Child characteristics		
Gender (female)	0.49	0.49
Child's age when CCT arrived	7.08	6.97
at municipality	[2.95]	[2.93]
Exposed to at least 1-month	0.88	0.88
weather shock (dummy)		
Duration of early-life shocks (months)	7.97	8.12
	[5.78]	[5.83]
Exposed to at least 1-month	0.88	0.88
weather shock (dummy)		
Exposed to 8-months	0.50	0.51
weather shock (dummy)		
Continued enrollment	0.57	0.57
ICFES Exam score (points)	44.47	44.33
	[5.74]	[5.71]
N	259,347	68,884

Note: “Full Sample" refers to all families in SISBEN Levels 1 and 2 in the urban segments of the municipality. “RD sample” refers to the optimal bandwidth sample around the cutoff of the CCT used in the RD framework. The period of early life is defined as the period from in utero up to age 3.

Table A.3: The Association between Weather Shocks Macroeconomic Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	*N of Unmet Basic Needs*			*N of Effective Political Parties*		
Weather shock	0.0181			0.0045		
	[0.0548]			[0.0086]		
Weather shock - lag		0.0202			-0.0036	
		[0.0572]			[0.0074]	
Weather shock - lead			0.0131			0.0025
			[0.0470]			[0.0063]
N	6856	6836	6856	7357	7336	7357
Outcome:	*Taxes per capita (pesos 2000)*			*Internally Displaced Populations*		
Weather shock	15.571			0.0005*		
	[83.830]			[0.0003]		
Weather shock - lag		69.265			0.0004	
		[76.111]			[0.0004]	
Weather shock - lead			-12.272			0.0003
			[75.146]			[0.0003]
N	6360	6342	6360	4184	4180	4181
Outcome:	*Primary education coverage*			*Secondary education coverage*		
Weather shock	0.0010			-0.0002		
	[0.0010]			[0.0003]		
Weather shock - lag		0.0007			0.0001	
		[0.0006]			[0.0002]	
Weather shock - lead			0.0002			0.0001
			[0.0007]			[0.0002]
N	5241	5241	5241	5250	5250	5250
Outcome:	*Department GDP per capita*					
Weather shock	0.021					
	[0.016]					
Weather shock - lag		-0.005				
		[0.018]				
Weather shock - lead			0.012			
			[0.009]			
N	7,329	7,329	7,329			
Municipality FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Note: The table shows regressions on the associations between weather shocks and macroeconomic variables.

Table A.4: Covariates around the cutoff

	Child is female	Child's age when first observed	Months of weather shocks	Head is young (age<30)	Household size
	(1)	(2)	(3)	(4)	(5)
Elegibility	-0.0033	-0.0293	-0.0236	0.0182	0.1067
	[0.0092]	[0.0200]	[0.0490]	[0.0210]	[0.0773]
N	68,884	68,884	68,884	68,884	68,884

(continued...)

	Head has no education	Head has primary educ	Head is married	Has access to water or sewage
	(6)	(7)	(8)	(9)
Elegibility	0.0003	0.0166*	0.0163	0.0188**
	[0.0112]	[0.0090]	[0.0111]	[0.0078]
N	68,767	68,767	68,884	68,884

Note: The sample includes families in the urban segment of CCT municipalities in SISBEN Levels 1 and 2 around the cutoff.

Table A.5: The Association between CCT Rollout and Family Characteristics

	Child is female	Child's age when 1st observed	Head's age <30	Head's age >55	Head has primary educ
	(1)	(2)	(3)	(4)	(5)
Exact month of CCT rollout	-0.0009 [0.0009]	0.0016 [0.0025]	0.0011 [0.0011]	-0.0008 [0.0008]	-0.0018 [0.0011]
N	68,884	68,884	68,884	68,884	68,884

(continued...)

	Head is married	Has access to water/sewage	Household size	Weather shock exposure	SISBEN score
	(6)	(7)	(8)	(9)	(10)
Exact month of CCT rollout	-0.0008 [0.0009]	-0.0005 [0.0004]	0.0107 [0.0087]	-0.0040 [0.0039]	0.0053 [0.0037]
N	68,884	68,884	68,884	68,884	68,884

Note: The sample includes children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN cutoff score). Models include municipality, month, and year of birth FE; standard errors are clustered at the municipality level. "Exact month of CCT rollout" captures the exact month when the program arrived to a particular municipality during Phase I, where 0 months means the arrival of the program to the first participant municipality (December 2000), and 28 months means the last participant municipality to receive the program (April 2003). "Weather shock exposure" is measured as the number of months a child was exposed to extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation distribution) during the events of interest (i.e., *El Niño* and *La Niña* shocks of the 1990s) from in utero to age 3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.6: First Stage: The Effects of CCT Eligibility on CCT Take-up

	CCT Take-up	
Sample for:	Continued Enrollment	ICFES Exam (SD)
	(1)	(2)
CCT Eligible	0.2743***	0.2947***
	[0.0131]	[0.0109]
N	68,884	26,386
Effect size	27.4%	29.5%
F-statistic	440	730

Note: The sample varies by each outcome's sample. CCT eligibility is defined as a dummy that takes the value of 1 when a household's SISBEN score is below the cutoff for the CCT, and 0 otherwise. CCT Take-up is defined as a dummy that takes the value of 1 when a household enrolls to receive *Familias en Acción* and receives the cash transfer (as observed in the *Familias en Acción* data on program beneficiaries), and 0 otherwise. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.7: Probability of Taking the ICFES Exam

	Taking ICFES Exam		
	(1)	(2)	(3)
CCT	0.1523*	0.1520*	0.1460
	[0.0908]	[0.0908]	[0.0918]
Weather Shock Utero to Age 3		-0.0026	-0.0030
		[0.0020]	[0.0023]
CCT * Shock Utero to Age 3			0.0013
			[0.0032]
N	39979	39979	39979
Mean	0.654	0.654	0.654

Note: The sample corresponds to the cohorts of children included in the ICFES estimations, which correspond to those born between 1988 and 1995 as they would be old enough to have taken the exam by 2014. The outcome is defined as an indicator equal to one if a child in those cohorts is observed in the ICFES data. Children in the sample are located in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN cutoff score).

Table A.8: Summary of outcomes and dataset

Educational outcome	Definition	Dataset	Years	Cohorts
Continued enrollment	Indicator for whether a child is observed across all years in the data (or until he/she completes high school) and zero otherwise (i.e., if a child drops out of school).	The universe of students in Colombia's public schools (R-166)	2005-2015	1988-2000
ICFES exam test scores	Average score across all individual subjects (math, language, biology, etc.) evaluated in the end-of high- school exam	ICFES Dataset	2005-2014	1988-1995
On-time grade completion: grades 7th, 8th, and 9th	Compares a child's age at the end of a specific grade with the "optimal" age	The universe of students in Colombia's public schools (R-166)	2005-2015	1988-2000

B Potential Mechanisms

In this section, we study potential mechanisms by which exposure to the extreme weather shocks could affect long-term educational outcomes. To conduct these analyses, we rely on auxiliary data from the *Population Census* 2005, the *Vital Statistics Birth Records* (VSBR) 1998, 1999, and 2000, the *Demography and Health Surveys* (DHS) 1990, 1995, 2000, and 2005, the *Colombian Survey of Health and Nutritional Status* (ENSIN) 2010, and the baseline wave of the *Familias en Acción* household survey (see Attanasio et al., 2004; García and Hill, 2010).[41]

Family economic resources. We begin by analyzing the association between weather shocks and family resources as measured by household income, poverty (SISBEN score), home ownership, and labor market participation (for the household head) using the SISBEN data.[42] In these analyses, because the focus is the family rather than the child, we use a different specification from that used in equation 2, which includes the current and lagged effects (up to 4 years) of the weather shocks. Appendix Table B.1 shows that being exposed to *El Niño* and *La Niña* reduces current household income by 1.14% per month of exposure, with little evidence of a persistent effect over time. No effects were found on other economic measures (including the SISBEN poverty score), which suggests that the impact of the weather shock may not be long-lasting.

Nutrition and child's health. A child's health is an important input in human capital formation (Bleakley, 2010), thus it constitute a key mechanism underlying the long-term effects of early-life weather shocks. We explore the impacts of these shocks on: (i) nutrition investments and (ii) child's health in the short, medium, and long term.

Using data from the 2000 baseline panel survey, we find some evidence that families of children who were exposed to the shock were less likely to spend money on food (a 2.4% decline per month of exposure), and in particular to spend less on grains, fruits, and vegetables, which are perishable and therefore less likely to be in supply during weather shocks (Appendix Table B.2).

Regarding child's health at birth, using data from the DHS, we find that while exposure to the weather shock during pregnancy is not associated with changes in prenatal care visits,

[41] These sources of data can be obtained here: (i) Census: https://international.ipums.org/international/. (Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 7.0 [dataset]. Minneapolis, MN: IPUMS, 2018. http://doi.org/10.18128/D020.V70.); (ii) VSBR: https://www.dane.gov.co/index.php/estadisticas-por-tema/salud/nacimientos-y-defunciones/nacimientos; (iii) DHS: https://dhsprogram.com/data/; (iv) ENSIN: the Colombian Family and Child Welfare Institute - *ICBF*; v) *Familias en Acción* household survey: the Colombian National Planning Department.

[42] A caveat of using the SISBEN data to analyze household income is that this variable is misreported because: (i) most low-income families are employed in the informal sector and (ii) income is self-reported.

it increases the probability of low birth weight and being preterm (Appendix Table B.3).[43] Also, it seems to reduce the probability that infants are breastfed for 6 months or longer.

Next, we explore the effects on health outcomes at later developmental stages. Using data from the DHS, when children were under age 5, we find that exposure to weather shocks early in life reduces their height-for-age (HAZ) by 0.16 SD (Appendix Table B.4). Using data from the ENSIN 2010, we examine whether the health effects of the weather shock are likely to persist over time. We find that exposure to early-life weather shocks reduce young adults' height and the probability of being overweight[44] for individuals aged 8–22 by 0.10 SD and one-third of a percentage point, respectively (columns 3-5 in Appendix Table B.4).[45]

[43] In further analyses, we examined the association between weather conditions and child mortality due to causes potentially associated with the weather shocks (i.e., respiratory or infection-related diseases) using the *Vital Statistics Death Records* 1998, 1999, and 2000. We found that the shock in early childhood has a positive but not statistically significant effect on mortality due to these diseases. We then discriminate the cause of child mortality by the type of shock (i.e., deaths due to respiratory-related diseases are more likely to occur during droughts, whereas deaths due to infection-related diseases are more likely to occur during floods). We found that exposure to droughts was associated with an increase in deaths due to respiratory causes, and floods exposure was associated with an increase in deaths due to infection. These results are not shown but are available upon request.

[44] Overweight is defined as a dummy variable that takes the value of one when an individual's body mass index (BMI; mass in kilograms divided by height in meters squared) exceeds 24 for those aged 18+ and for those below age 18, the international BMI cutoff varies by age as specified by the World Health Organization.

[45] We also examined the effects of weather shocks on the probability of being underweight (i.e., BMI<18.5) and we found a small decline of 2.7% although not statistically significant.

Table B.1: Effects of Early-life Weather on Household Economic Resources

	ln(HH income)	Sisben score	Home ownership	Head works
	(1)	(2)	(3)	(4)
Weather Shock in t	-0.0114*	-0.0018	0.0001	-0.0007
	[0.0067]	[0.0069]	[0.0031]	[0.0017]
Weather Shock in t-1	-0.0146	0.0014	-0.0012	-0.0036
	[0.0101]	[0.0081]	[0.0047]	[0.0041]
Weather Shock in t-2	-0.0184	0.0084	0.0072	-0.0015
	[0.0118]	[0.0101]	[0.0070]	[0.0052]
Weather Shock in t-3	-0.0184	-0.0045	0.0156	0.0028
	[0.0167]	[0.0171]	[0.0136]	[0.0054]
Weather Shock in t-4	-0.0062	0.0167	0.0129	-0.0047
	[0.0200]	[0.0246]	[0.0094]	[0.0052]
N	71,958	71,958	71,958	66,748
F-stat	0.71	0.52	1.79	2.41
p-val	0.61	0.76	0.12	0.03
Mean	11.49	36.88	0.29	0.94

Note: The sample includes families of children in our main specifications. Models control for child's gender, household head education level, marital status, family size, access to water or sewer system, and year, month, municipality of SISBEN interview. "Head works" is defined for the active population (those working and looking for work). Weather shock refers to the number of months of exposure to floods/droughts shocks during the *El Niño* and *La Niña* events. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.2: Effects of Early-life Weather on Household Food Consumption Using the CCT Baseline Survey

	ln($ spent on...				
	animal protein)	carbs)	grains)	fruits, veggies)	total food)
	(1)	(2)	(3)	(4)	(5)
Weather Shock	-0.0157	-0.0156	-0.0343***	-0.0266*	-0.0244**
Utero Age 3	[0.0131]	[0.0140]	[0.0118]	[0.0144]	[0.0109]
N	1,436	1,414	1,477	1,443	1,477
Mean (log pesos)	9.54	8.19	7.54	8.42	10.1

Note: The sample includes all children in the baseline wave of the CCT *Familias en Acción* household survey collected in 2000 (before the program started). The sample is restricted to families living in the urban segment of the CCT municipality. Models control for child's gender and age in months, mother's age, education, and relationship status; all models include municipality, month, and year of child's birth FE. Weather shock refers to the number of months a child was exposed to the flood/drought shocks during the *El Niño* and *La Niña* events from in utero to age 3. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.3: Effects of Early-life Weather on Prenatal Care, Health at Birth, and Breastfeeding Using the DHS and VSBR Datasets

	Prenatal care y/n	Prenatal care visits>=4	Breastfeed y/n	Breastfeed >6 months	LBW (BW<2,500 gr)	VLBW (BW<1,500 gr)	Preterm (weeks<37)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Weather Shock	0.0010	-0.0116	0.0001	-0.0160**	0.0006	0.0002***	0.0015**
Utero	[0.0059]	[0.0088]	[0.0030]	[0.0076]	[0.0004]	[0.0008]	[0.0007]
N	1,749	1,411	1,749	1,749	167,479	167,479	166,030
Mean	0.78	0.73	0.96	0.60	0.047	0.01	0.08
Dataset	DHS	DHS	DHS	DHS	VSBR	VSBR	VSBR

Note: The sample includes all children in DHS 1995, 2000, and 2005 and all births in the Vital Statistics Birth Records (VSBR) 1998, 1999, and 2000. The sample is restricted to families living in the urban segment of the CCT municipalities. Models include as covariates child's gender and age in months, mother's age, education, relationship status, and dummy for DHS (or VSBR) wave; all models include municipality, month, and year of child's birth FE. The models using VSBR also include controls for health insurance and birth order. Weather shock refers to the number of months a child was exposed to the flood/drought shocks during the *El Niño* and *La Niña* events in utero. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.4: Effects of Early-life Weather on Children's Health in the Medium Term (MT) and Long Term (LT) Using the DHS and ENSIN Datasets

	Height-for-Age (Z-scores)	Weight-for-Age (Z-scores)	Height (Z-scores)	Body Mass Index	Overweight (BMI<25)
	MT	MT	LT	LT	LT
	(1)	(2)	(3)	(4)	(5)
Weather Shock	-0.0201**	-0.0170	-0.0130*	0.0292	0.0055*
Utero to Age 3	[0.0080]	[0.0155]	[0.0075]	[0.0261]	[0.0032]
N	4,012	1,968	2,764	2,411	2,135
Mean (SD)	-0.60	-0.26	-0.06	19.55	0.13
Effect size (SD)	-0.16		-0.10		0.33%
Datset	DHS	DHS	ENSIN	ENSIN	ENSIN

Note: The sample includes all children below age 5 in the 1995, 2000, and 2005 DHS data, while models using the ENSIN include children born between 1988 and 2000. The sample is restricted to families living in the urban segment of the CCT municipalities. Models control for child's 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. Weather shock refers to the number of months a child was exposed to the flood/drought shocks during the *El Niño* and *La Niña* events from in utero to age 3. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

C Selection checks

This Appendix Section presents evidence related to potential selection concerns.

C.1 Selection Concerns: Mobility

Table C.1: Effects of Early-life Weather on Mobility

	Moves	
	(1)	(2)
Weather Shock Utero to Age 3	-0.0007	-0.0036
	[0.0006]	[0.0033]
Weather Shock * Mom's educ=No educ		0.0005
		[0.0008]
Weather Shock * Mom's educ=primary		0.0007
		[0.0008]
Weather Shock * Mom is married		0.0009*
		[0.0005]
Weather Shock * Mom's age		-0.000
		[0.0001]
Weather Shock * Mom's age squared		-0.000
		[0.00001]
Weather Shock * Household size		-0.0002***
		[0.0001]
N	68,312	68,312
Mean	0.30	0.30

Note: See Table 4 for more information on the sample and controls. Migrants are defined as those who were born in a different municipality from where they were sampled in the SISBEN data. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.2: The Effects of CCTs on Mobility

	Moves	
	(1)	(2)
CCT Eligibility	0.0089	-0.0083
	[0.0056]	[0.0283]
CCT Eligibility * Mom's educ=No educ		0.0195
		[0.0139]
CCT Eligibility * Mom's educ=primary		0.0128
		[0.0106]
CCT Eligibility * Mom is married		0.0073
		[0.0069]
CCT Eligibility * Mom's age		0.0002
		[0.0012]
CCT Eligibility * Mom's age squared		0.000
		[0.00001]
CCT Eligibility * Household size		-0.0017*
		[0.0019]
N	68,312	68,312
Mean	0.30	0.30

Note: See Table 4 for more information on the sample and controls. Migrants are defined as those who were born in a different municipality from where they were sampled in the SISBEN data. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

C.2 Fertility

Table C.3: The Effects of Weather Shocks on Fertility using **Census** and **Vital Statistics Data**

	Cohort size	Sex ratio	Cohort size	Sex ratio	Child is female	Mother's age 12 -24	Mother's age 25 - 29	Mother's education <=primary	Mother's education >=HS	Mother is single
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Shock t=-3	0.7513	-0.9127	-0.4111	-0.1396	0.1376	0.0331	-0.1072	-0.0754	0.0871	0.1787
	[0.7132]	[2.1008]	[0.4124]	[0.6588]	[0.1555]	[0.1424]	[0.1232]	[0.1590]	[0.1027]	[0.1106]
Shock t=-2	0.4985	1.9838	0.0403	0.1249	0.0178	0.1230	-0.0325	0.1290	0.0438	-0.1297
	[0.6832]	[1.9565]	[0.3469]	[0.5726]	[0.1455]	[0.1398]	[0.1159]	[0.1446]	[0.0940]	[0.1021]
Shock t=-1	0.8319	1.7974	0.0095	0.2188	-0.0707	0.2419	-0.0337	0.0319	-0.0728	-0.1719
	[0.7301]	[1.9028]	[0.4316]	[0.7197]	[0.1828]	[0.1682]	[0.1367]	[0.1700]	[0.1109]	[0.1368]
Shock t= 0	-0.1045	-0.8151	-0.0596	0.2188	0.0665	0.3119*	-0.0018	0.1074	-0.0444	-0.0632
	[0.5634]	[1.6264]	[0.5294]	[0.7197]	[0.1703]	[0.1669]	[0.1425]	[0.1827]	[0.1132]	[0.1228]
Shock t=1	0.7100	1.2063	0.2591	-0.4558	0.1505	0.2991	-0.0525	0.3040	-0.1798	-0.0823
	[0.5816]	[1.7401]	[0.5127]	[0.6711]	[0.1835]	[0.1824]	[0.1532]	[0.1982]	[0.1277]	[0.1512]
Dataset	Census	Census	VS	VS	VS	VS	VS	VS	VS	VS
N	6,041	6,041	19,608	19,608	19,608	19,608	19,608	19,608	19,608	19,608
Outcome mean	206.0	112.2	276.7	112.7	49.3	56.3	20.7	58.7	13.8	17.5

Note: The table shows regressions on the effect of weather shocks on fertility outcomes using the 2005 Census and Vital Statistics (VS) Records, 1998-2000. All the outcomes are in log's. Cohort size is defined as the total number of births in a municipality-year-month; sex ratio is the ratio of male births vs. female births; outcomes in columns (3)-(8) Models include municipality, year, and month fixed effects and municipality linear time trends. Errors are clustered at the municipality level.

Table C.4: Effects of Early-life Weather on Fertility

	Total fertility after "focal" child		Birth spacing after "focal" child	
	(1)	(2)	(3)	(4)
Weather Shock Utero to Age 3	-0.0038	0.0077	0.1168	-0.0808
	[0.0032]	[0.0297]	[0.0625]	[0.2530]
Weather Shock * Mom has no educ		0.0102		0.1965
		[0.0062]		[0.0885]
Weather Shock * Mom has primary educ		0.0074		0.1093
		[0.0056]		[0.0704]
Weather Shock * Mom is married		0.0025		-0.0709
		[0.0021]		[0.0435]
Weather Shock * Mom's age		-0.0006		0.0022
		[0.0014]		[0.0116]
Weather Shock * Mom's age squared		-0.000		-0.000
		[0.0000]		[0.0001]
N	68,146	68,146	32,426	32,426
Mean	0.78	0.78	29.85	29.85

Note: See Table 4 for more information on the sample and controls. Total fertility after "focal" child refers to the number of younger siblings a child in our sample has. Birth spacing after "focal" child refers to the number of months in between a child in our sample and the next younger sibling (following birth order). It is worth noting that the outcome mean refers to the number of children that a mother has (in the DHS data), after a focal child. Thus, this statistic does not reflect the total fertility in Colombia. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.5: The Effects of CCTs on Fertility Outcomes

	Total fertility after "focal" child		Birth spacing after "focal" child	
	(1)	(2)	(3)	(4)
CCT Eligibility	0.0437*	-0.1493	-0.3011	4.243
	[0.0234]	[0.2150]	[0.5725]	[3.418]
CCT Eligibility*Mom's educ=No educ		0.0382		-1.125
		[0.0544]		[0.996]
CCT Eligibility*Mom's educ=primary		0.005		-0.794
		[0.0524]		[0.875]
CCT Eligibility*Mom is married		0.0450*		-0.511
		[0.0259]		[0.547]
CCT Eligibility*Mom's age		0.0052		-0.166
		[0.0104]		[0.135]
CCT Eligibility*Mom's age squared		0.000		0.002
		[0.0001]		[0.001]
N	68,146	68,146	32,173	32,173
Mean	0.78 children		29.85 months	

Note: See Table 4 for more information on the sample and controls. Total fertility after "focal" child refers to the number of younger siblings a child in our sample has. Birth spacing after "focal" child refers to the number of months in between a child in our sample and the next younger sibling (following birth order). It is worth noting that the outcome mean refers to the number of children that a mother has (in the DHS data), after a focal child. Thus, this statistic does not reflect the total fertility in Colombia. Standard errors are clustered at the municipality level. $***p< 0.01$, $**\ p< 0.05$, $*p< 0.1$.

C.3 Mortality

Table C.6: Effects of Early-life Weather on Infant and Child Mortality in the DHS

	Child died in 1st month		Child died by age 1		Child died by age 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Weather Shock	0.0012	0.0187	-0.0002	-0.0108	0.0003	0.0041
	[0.0011]	[0.0125]	[0.0011]	[0.0149]	[0.0011]	[0.0212]
Weather Shock * Mom has primary educ		-0.0041		0.0086		0.0048
		[0.0046]		[0.0062]		[0.0039]
Weather Shock * Mom has HS or <		-0.0040		0.0068		0.0051
		[0.0047]		[0.0062]		[0.0040]
Weather Shock * Mom has >HS		-0.0056		0.0076		0.0058
		[0.0048]		[0.0063]		[0.0041]
Weather Shock * Mom is married		-0.0030		-0.0013		-0.0013
		[0.0022]		[0.0015]		[0.0022]
Weather Shock * Mom's age		-0.0010		0.0003		-0.0008
		[0.0009]		[0.0010]		[0.0013]
Weather Shock * Mom's age squared		-0.0000		-0.0000		-0.0000
		[0.0000]		[0.0000]		[0.0000]
Weather Shock * Household size		0.0004		-0.0003		0.0002
		[0.0005]		[0.0006]		[0.0006]
N	9,194	9,194	7,284	7,284	3,402	3,402

Note: The sample includes children below age 5 in the 1990, 1995, and 2000 DHS data and in the urban segment of the CCT municipalities. Models control for child's gender and age, mother's education, age, marital status, household size, and child's year, month, and municipality of birth FE. Since the DHS does not include municipality of birth, we restrict the sample to children of families living in the current municipality for a longer period than a child's age. Weather shock refers to the number of months a child was exposed to the flood/drought shocks during the *El Niño* and *La Niña* events. Columns 1 and 2 only captures the in utero period, whereas columns 3 and 4 capture the period from in utero up to age 1, and columns 5 and 6 from in utero up to age 3. The sample in columns 3 and 4 is restricted to ages 1+, whereas columns 5 and 6 include children 3+. Regressions are weighted using DHS person weights. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.7: Effects of Early-life Weather on Selective Survival in the Population Census

	Cohort size		Sex ratio	
	Urban areas	Urban areas and CCT municipalities	Urban areas	Urban areas and CCT municipalities
	(1)	(2)	(3)	(4)
Weather Shock Utero to Age 3	-0.0103	-0.0116	0.0005	-0.0014
	[0.0206]	[0.0092]	[0.0021]	[0.0027]
N	26,428	16,371	26,428	16,371

Note: The sample includes information from the population Census 2005 at the municipality-year-month level and is restricted to urban areas only. Models include municipality, month, and year of birth FE. The Weather Shock variable refers to the number of months a child was exposed to the flood/drought shocks during the *El Niño* and *La Niña* events from in utero to age 3. 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 females born in a given municipality, year, and month. Data were downloaded from IPUMS International. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

D Robustness checks

This Appendix Section presents further evidence that our results are robust to different specifications of both the weather shock and CCTs, to using different bandwidths in our RD framework, and to accounting for potential confounding factors (i.e., exposure to violence and selective matching across datasets).

D.1 Using Alternative Definitions of Weather Shocks

We study the robustness of empirical results to the definition of the weather shocks by testing the following specifications: (i) including other thresholds of rainfall shock exposure (i.e., changes in precipitation between the 60th and 80th percentile and between the 20th and 40th percentiles); (ii) separating the shocks between droughts and floods; and (iii), using different cutoffs to define extreme weather (+/- one standard deviation instead of the upper 80th or the lower 20th percentile). These results are reported in Table D.1 Panels B to D (Panel A shows our main results described above), and they suggest that the effects on children's education are robust to using these alternative definitions. Panel B, for instance, shows that adding "extra" windows of exposure to changes in precipitation (i.e., including changes in rainfall between the 40th percentile to the 60th percentile) has no additional effects on children's outcomes; the magnitudes of the coefficients are small and not statistically significant. Panel C indicates that separating floods and droughts in our main specification leads to remarkably symmetric effects on the outcomes, which suggests that both type of shocks are detrimental for human capital formation. For example, the point estimate of the impact of drought exposure on the probability that a child remains enrolled in school is -0.0039 and statistically significant at the 5% level, whereas that of flood exposure is -0.0029 and statistically significant at the 1% level. Last, in Panel D we show that, using +/- one standard deviation shocks instead of the 80th and 20th percentile precipitation cutoffs provides estimates within the range of those obtained using our main specification (Panel A).[46] [47]

D.2 Using Alternative Definitions of CCT Exposure

We examine an alternative definition of exposure to the CCT program by using the number of months a child is enrolled in the program (instead of a participation dummy, as in our main specification), obtained from the System of Beneficiaries of the CCT program administrative data. As in the case of participation in the CCT program, duration in the program is also endogenously determined. Therefore, to estimate the effects of length of participation

[46] We also examined the presence of nonlinearities in weather shocks by including the squared term of the shocks in the equation. We found little evidence of nonlinearities (results not shown).

[47] We also estimated alternative specifications in which we measured the shock using the intensity of precipitation (in millimeters of rain) above the thresholds. Thus, instead of using a binary definition for each month and then adding the number of months of shocks during *El Niño* and *La Niña*, we considered the total millimeters of extreme precipitation a child was exposed to during these events. Results from these specifications provide estimates that, although they tend to be smaller in magnitude, are within the range of those obtained from the main specification. In other words, using a more flexible specification that accounts for the intensive margin of the shock in millimeters of rainfall leads to similar effect sizes on the outcomes.

in the CCT program, we instrument treatment dosage by exploiting variation in potential exposure to the program taking into account the timing of the CCT rollout across municipalities, the age of the child at rollout, and the fact that Phase I ended in December 2005. Table D.2 reports these results, which confirm that the longer the duration, the greater the gains in children's education. Using the average duration in the CCT, which is 4 years in Phase I, we compute effect sizes that are substantially similar to those obtained from our main specification (shown in the top panel).

D.3 Other robustness checks

We perform additional robustness checks to validate our findings. We estimate specifications without socio-demographic covariates and including municipality-specific trends. Also, we estimate specifications with alternative bandwidths. In particular, we use bandwidths of 2 and 4 SISBEN points around the cutoff. Appendix Figure D.1 summarizes the results from these robustness checks and shows that our results (depicted in blue) are robust to these alternative specifications. In addition, we present placebo checks that include in our regressions exposure to extreme weather events during the period prior to conception (which should not affect children) or at older ages (which are less detrimental) and their interaction with the CCT. Appendix Tables D.3 and D.4 show that our main results are robust to the inclusion of exposure to shocks across other periods, and those estimates are small and statistically insignificant.

D.4 Potential confounders

Exposure to Violence One potential threat to the validity of our results could be exposure to violence shocks, because Colombia has faced an internal armed conflict for over five decades, which has extended to nearly all regions of the country.[48] To examine whether violence could be a relevant omitted variable, we directly control for violence exposure in our DD specification of the weather shocks, using average homicide rates from in utero to age 3. Results are shown in Appendix Table D.5. For comparison purposes, we also present our main estimates of weather shocks (i.e., those shown in Table 3). Overall, we find that our main estimates do no seem to change when we account for children's violence exposure.

Selective Matching across Administrative Datasets Because we use administrative data from multiple sources, we examine whether the probability of data matching is correlated with weather shocks or CCT eligibility, which could bias our results. To assess this issue, we construct a sample matched indicator that takes the value of one for children in the SISBEN data, born in the years of interest, and observed in the Ministry of Education records and zero otherwise (i.e., being in the SISBEN data and having been born in the 1990s, but not found in the Education records), and we examine the association between this indicator and being exposed to weather shocks early in life and/or being eligible to receive CCTs. In

[48] Previous research has shown that early-life exposure to violence can have negative and persistent impacts on health, education, and labor market outcomes (Camacho, 2008; Duque, 2017).

Appendix Table D.6, we regress this indicator on: (i) exposure to the weather shock and its interaction with socio-demographic characteristics (columns 1 and 2); (ii) eligibility for CCTs and its interaction with socio-demographic characteristics (columns 3 and 4); (iii) both "treatments" (column 5); and (iv) the interaction between the weather shock and CCT eligibility (column 6). Results suggest little evidence that exposure to weather shocks, eligibility for the CCT program, or their interaction are correlated with selective matching. However, we do find a couple of significant correlations. For instance, children in larger families and who were exposed to the weather shock are more likely to appear in the matched sample (0.3%), and children whose parents were married and were eligible for the CCT were less likely to be in the matched sample (2.6%). Given the small magnitude of these correlations, we are not concerned about selective matching inducing a significant bias in our estimates.

Table D.1: Effects of Early-Life Weather on Children's Education Using Alternative Definitions of Weather Shock Exposure

	Continued enrollment	ICFES score (SD)
	(1)	(2)
Panel A: Main specification		
Weather Shock Utero to Age 3	-0.0035***	-0.0057**
	[0.0011]	[0.0033]
Effect size	-5.0%	-0.05 SD
Panel B: Main specification + additional thresholds of exposure		
Weather Shock (percentile 80-20)	-0.0050***	-0.0590**
Utero to Age 3	[0.0008]	[0.0030]
Weather Shock (percentile 60-40)	0.0014	-0.0018
Utero to Age 3	[0.0010]	[0.0031]
Effect size	-10.5%	-0.05 SD
Panel C: Separating between droughts and floods		
Weather Shock (Droughts in percentile 0-20)	-0.0039**	-0.0254***
Utero to Age 3	[0.0009]	[0.0093]
Weather Shock (Floods in percentile 80-100)	-0.0029***	-0.0074*
Utero to Age 3	[0.0010]	[0.0041]
Effect size	-6.3%	-0.081 SD
Panel D: 1 SD shocks (outside +/- 1 SD)		
Weather Shock Utero to Age 3	-0.0030***	-0.0101***
	[0.0011]	[0.0043]
Effect size	-6.1%	-0.084 SD
N	68,884	26,386
Mean	0.57	0 SD

Note: The sample includes children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN score cutoff). See Table 3 for more information on the sample and controls. The Weather Shock is measured using alternative definitions. Panel A (main specification): Weather Shock is measured as the number of months of extreme weather (where extreme weather is defined as a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation distribution) during the events of interest (i.e., *El Niño* and *La Niña* shocks of the 1990s) in the relevant developmental stages. Panel B (additional thresholds of exposure): Adds to the main specification the number of months of exposure to rainfall levels between the 80-60th and 20-40th percentiles. Panel C (separating floods and droughts): Similar to main specification but separating between shocks that occur at the upper tail (percentile 80-100, floods) vs. the lower tail (percentile 0-20, droughts) of the precipitation distribution. Panel D (using 1 SD shocks): Similar to main specification but defining the threshold using above 1 SD or below 1 SD of the monthly-municipality historical distribution during the events of interest (i.e., *El Niño* and *La Niña* shocks of the 1990s) in the relevant developmental stages. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

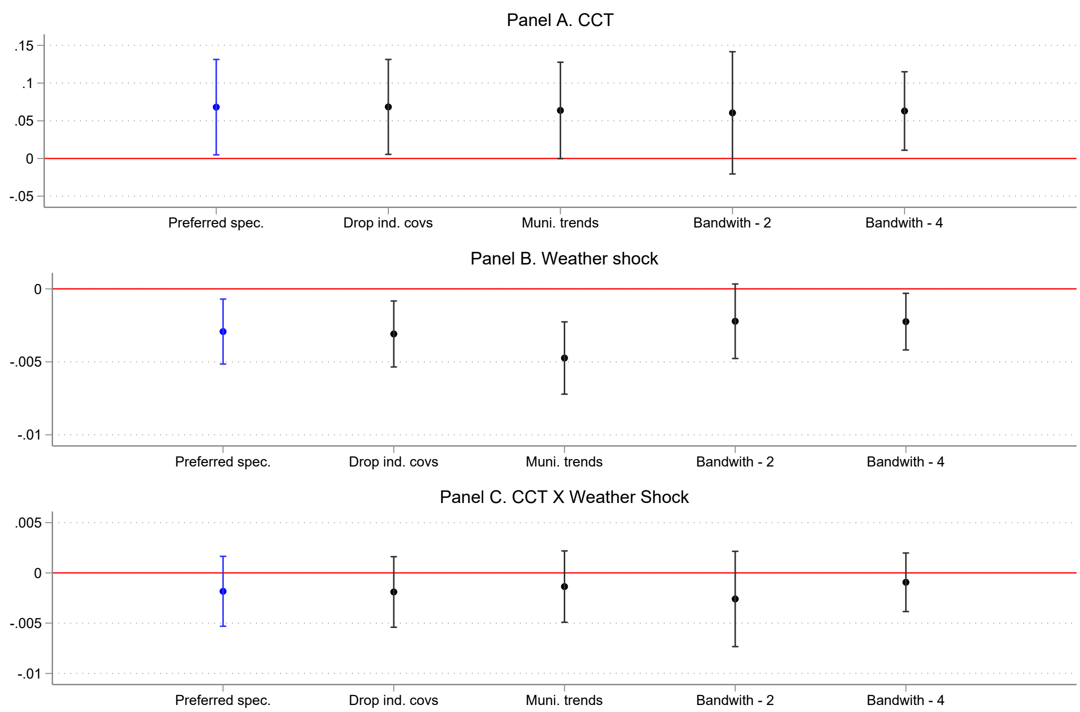
Table D.2: Effects of CCTs (measured in months) on Children's Education

	Continued Enrollment	ICFES score (SD)
	(1)	(2)
Main specification		
CCT Take-up	0.0538*	0.1904**
	[0.0289]	[0.0804]
Effect size	12.5%	0.19 SD
Using months in the program		
CCT Duration	0.0014**	0.0033*
	[0.0006]	[0.0017]
Effect size	15.6%	0.16 SD
N	68,884	26,386

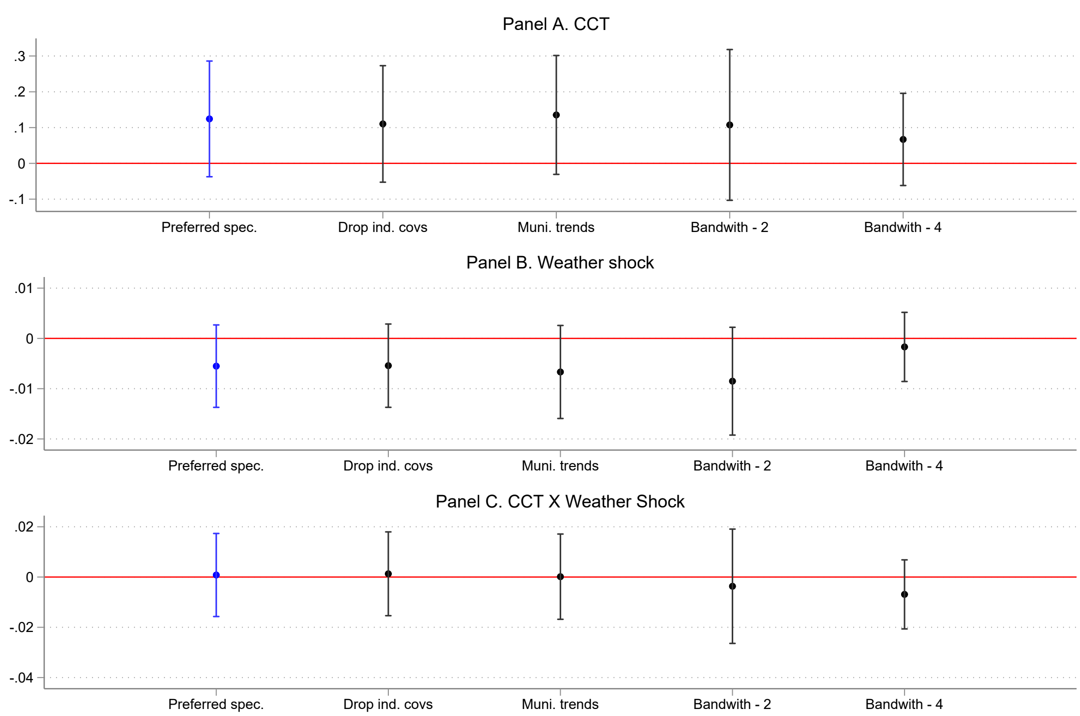
Note: See Table 4 for more information on the sample and controls. "CCT - Duration" refers to the number of months of actual participation in the CCT - Phase 1 that is instrumented with potential exposure to the CCT, calculated using CCT rollout date and child's age at rollout. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure D.1: Robustness Checks

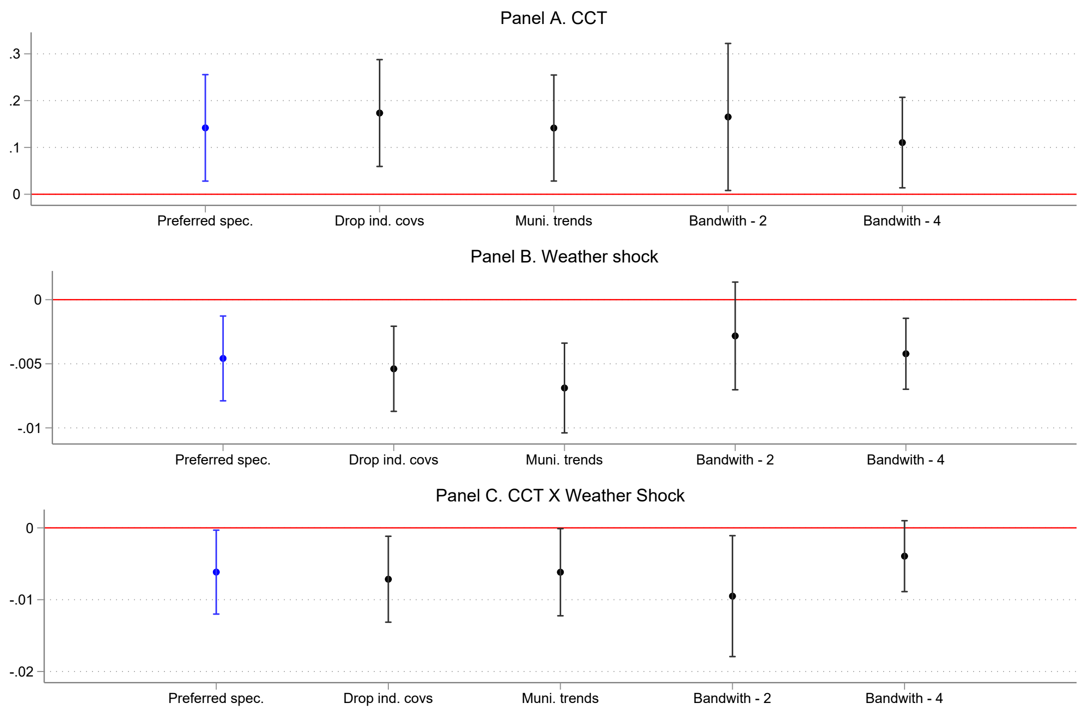
(a) Continued Enrollment



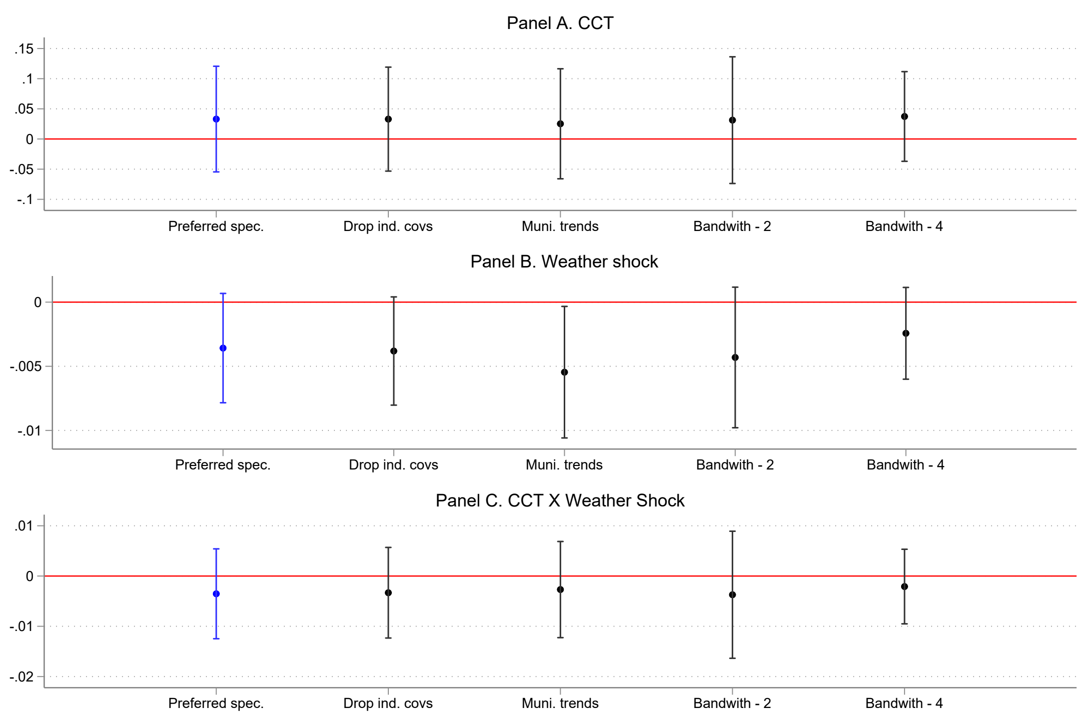
(b) ICFES Test Scores



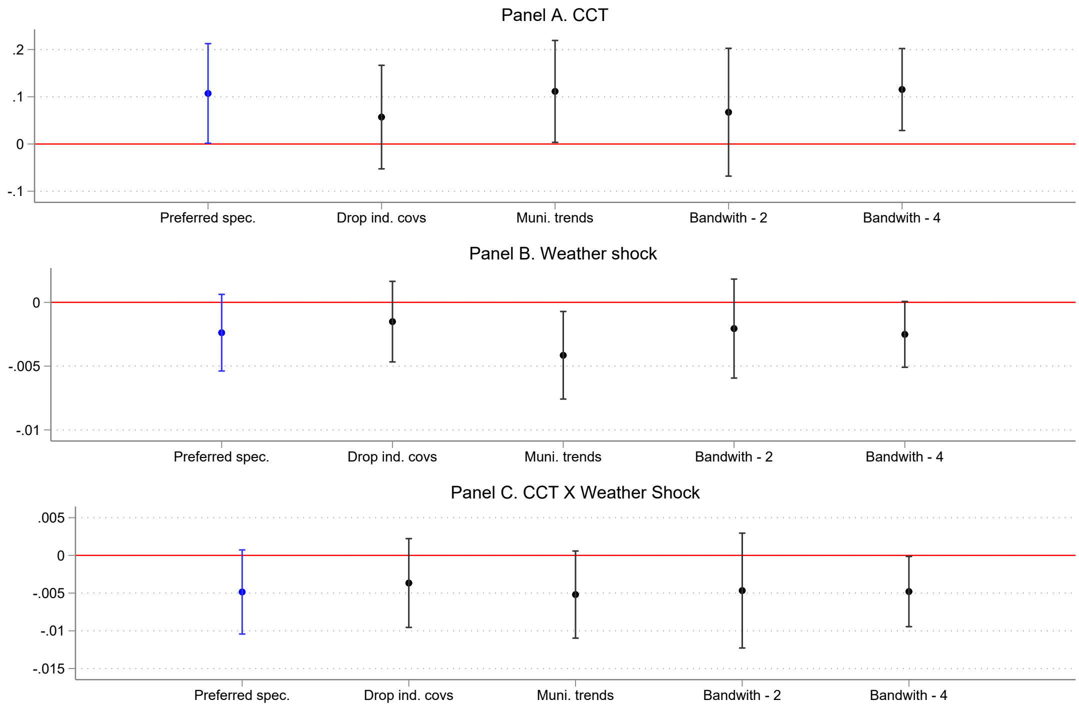
(c) Continued Enrollment - early



(d) Continued Enrollment - late



(e) Grade 8 on-time graduation - early



(f) Grade 8 on-time graduation- late

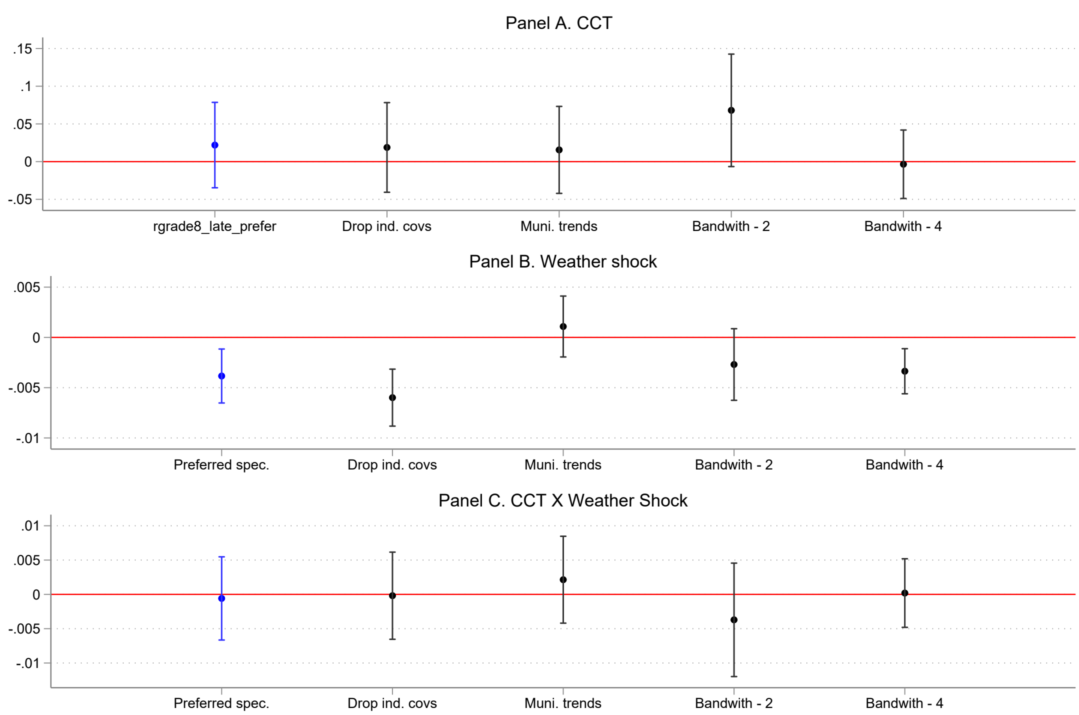


Table D.3: Placebo Checks: Weather Shock Exposure during Other Periods - Continued Enrollment and ICFES Score

	Continued enrollment		ICFES Exam	
	(1)	(2)	(3)	(4)
Weather Shock Utero to Age 3	-0.0032***	-0.0025*	-0.0058	-0.0031
	[0.0011]	[0.0013]	[0.0036]	[0.0044]
CCT	0.0209**	0.0358*	0.0362	0.0914
	[0.0099]	[0.0213]	[0.0263]	[0.0597]
CCT * Shock Utero to Age 3	-0.0008	-0.0011	0.0002	-0.0034
	[0.0007]	[0.0010]	[0.0035]	[0.0040]
Placebos				
Shock 1y pre-concep		0.0009		0.0029
		[0.0018]		[0.0040]
Shock Age 4-6		0.0011		0.0050
		[0.0015]		[0.0044]
Shock Age 7-10		-0.0004		-0.0048
		[0.0011]		[0.0035]
CCT * Shock 1y pre-concep		0.0008		-0.0038
		[0.0015]		[0.0043]
CCT * Shock Age 4-6		-0.0006		-0.0042
		[0.0010]		[0.0031]
CCT * Shock Age 7-10		-0.0012		0.0007
		[0.0009]		[0.0029]
N	68800	66511	27137	25655

Note: The sample includes children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN cutoff score).

Table D.4: Placebo Checks: Weather Shock Exposure during Other Periods - Continued Enrollment Early vs. Late

	Cont Enroll-Early		Cont Enroll-Late	
	(1)	(2)	(3)	(4)
Weather Shock Utero to Age 3	-0.0055***	-0.0078***	-0.0041**	-0.0046*
	[0.0015]	[0.0021]	[0.0018]	[0.0024]
CCT	0.0410**	0.0374	0.0115	0.0502
	[0.0162]	[0.0270]	[0.0144]	[0.0337]
CCT * Shock Utero to Age 3	-0.0020*	-0.0019	-0.0014	-0.0033
	[0.0010]	[0.0015]	[0.0019]	[0.0026]
Placebos				
Shock 1y pre-concep		-0.0026		-0.0021
		[0.0027]		[0.0018]
Shock Age 4-6		-0.0031		-0.0010
		[0.0023]		[0.0021]
Shock Age 7-10		-0.0034		-0.0003
		[0.0023]		[0.0017]
CCT * Shock 1y pre-concep		-0.0005		0.0023
		[0.0027]		[0.0020]
CCT * Shock Age 4-6		0.0009		-0.0023
		[0.0014]		[0.0017]
CCT * Shock Age 7-10		-0.0008		-0.0017
		[0.0015]		[0.0017]
N	36276	35494	30866	29415

Note: The sample includes children in the urban segment of CCT municipalities around the optimal bandwidth (+/- 3 points of SISBEN cutoff score).

Table D.5: Effects of Early-life Weather on Children's Education controlling for Violence Shocks

	Continued Enrollment		ICFES Exam score (SD)	
	(1)	(2)	(3)	(4)
Weather Shock	-0.0035***	-0.0036***	-0.0081**	- 0.0079**
Utero to Age 3	[0.0011]	[0.0011]	[0.0034]	[0.0037]
N	68,884	68,884	26,386	26,386
Violence controls		X		X

Note: See Table 3 for more information on the sample and controls. These estimations additionally control for the average homicide rate in a child's municipality of birth from in utero to age 3. Each column comes from a separate regression. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.6: Selective Matching, Early-life Weather, and CCT Eligibility

	Weather shock		CCT eligibility		Both shocks	Add interaction
	(1)	(2)	(3)	(4)	(5)	(6)
Weather Shock	0.0006	0.0009			0.0006	0.0008
Utero to Age 3	[0.0007]	[0.0023]			[0.0007]	[0.0007]
CCT Eligibility			0.0066	0.0103	0.0066	0.0090
			[0.0138]	[0.0327]	[0.0138]	[0.0143]
Shock * Female		0.0005		0.0021		
		[0.0004]		[0.0040]		
Shock * HH no educ		0.0012		0.0009		
		[0.0008]		[0.0100]		
Shock * HH educ=primary		0.0006		0.0065		
		[0.0007]		[0.0087]		
Shock * Household size		0.00017**		0.0011		
		[7.87e-05]		[0.0009]		
Shock * Water or sewage		-0.0006		-0.0010		
		[0.0015]		[0.0154]		
Shock * HH is married		-0.0005		0.0129**		
		[0.0005]		[0.0057]		
Shock * HH age		-0.0001		-0.0005		
		[0.0001]		[0.0012]		
Shock * HH age squared		1.46e-06*		4.10e-06		
		[8.86e-07]		[1.23e-05]		
Elegible * Weather						-0.0003
						[0.0004]
N	231,627	231,640	231,640	231,640	231,640	231,640
Mean	0.50	0.50	0.50	0.50	0.50	0.50

Note: The sample includes children in the SISBEN data and in the optimal bandwidth who are in the urban segment of the municipalities targeted by the CCT, Phase 1. The dependent variable is a dummy equal to 1 if a child appears in the Ministry of Education administrative data (R-166) or ICFES data. Models include municipality, month, and year of birth FE; errors are clustered at the municipality level. Control covariates include child's gender, age, household head education, age, family size, marital status, access to water/sewer system, and year of SISBEN interview dummies. Each column comes from a separate regression. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

E Empirical Results and the Theory on Human Capital Formation

In this section, we lay out a simple theoretical framework to analyze the empirical results of the paper.

Theoretical framework. Following Cunha and Heckman (2007) and Cunha et al. (2010)[49], the technology of skill formation can be modeled by:

$$\theta_{it+1} = f_t(\theta_{it}, I_{it}, x_i), \tag{6}$$

where $f(.)$ is a continuous and differentiable function; θ_{it} is the stock of child's i skills (e.g., health, cognition, etc.) measured at time t with $\frac{\partial f_t(.)}{\partial \theta_{it}} > 0$, also known as *self-productivity*[50]; $I_{it} > 0$ represents investments in child i in period t (e.g., nurturing care, vaccinations, etc.) with $\frac{\partial f_t(.)}{\partial I_{it}} \geq 0$; and x_i is a vector of parental characteristics (e.g., mother's education). Substituting backwards in (6) repeatedly we can express a child's stock of skills as a function of all previous investments:

$$\theta_{it+1} = m_t(\theta_{i1}, I_{i1}, ..., I_{it}, x_i). \tag{7}$$

The literature on human capital formation has used this framework to formally define two useful concepts. First, the idea of *sensitive* and *critical periods*. A *sensitive period* for θ_{t+1}, is that in which the returns of investments on human capital are the largest relative to other periods –i.e., $\frac{\partial \theta_{it+1}}{\partial I_{it^*}} > \frac{\partial \theta_{it+1}}{\partial I_{is}}$ for $s \neq t^*$ – e.g., that investments that come relatively early in a child's life (early childhood) have larger returns on his/her human capital outcomes than those made at later stages (adolescence). A *critical period* for θ_{t+1}, is that in which the returns of investments are positive while they are zero for periods different than that period –i.e., $\frac{\partial \theta_{it+1}}{\partial I_{it^*}} > 0$ and $\frac{\partial \theta_{it+1}}{\partial I_{is}} = 0$ for $s \neq t^*$. Second, the model displays *dynamic complementarities* if investments at a given period have larger returns when the stock of previous skills is higher – i.e., $\frac{\partial^2 f_t(.)}{\partial \theta_{it} \partial I_{it}} > 0$.

How do our empirical results relate to the theory on human capital formation? We start by embedding our empirical research design into the theoretical framework. To this end, we consider a simplified version of (7) with three consecutive time periods in an individual's life. In $t = 1$, children are exposed to the weather shock (denoted $\varepsilon_{i1}^{WeatherShock}$); in $t = 2$ some children receive the CCT-induced investment early (denoted ε_{i2}^{CCT}); and in $t = 3$, other children receive the CCT-induced investment later (denoted ε_{i3}^{CCT}). The outcome is measured at $t = 4$. Assuming a constant elasticity of substitution (CES) functional form

[49] This framework is also related to the work by Becker and Tomes (1986) and by Aiyagari et al. (2002), that conceived childhood as a unique period. Mogstad (2017) discusses the extension of Becker and Tomes (1986) model to multiple periods and multiple skills.

[50] *Self-productivity* implies that a given dimension of capacity may also affect the accumulation of another, distinct dimension (e.g., that children with better health endowment are more able to develop cognitive skills).

for $f(.)$, we can express a child's human capital production function as[51]

$$h_i = m(\theta_{i1}, [\eta_1(\underbrace{\overset{-}{I_{i1}(\varepsilon_{i1}^{WeatherShock})}}_{\substack{\text{Exposure}\\ \text{to adverse}\\ \text{weather shock}}})^{\phi} + \eta_2(\underbrace{\overset{+}{I_{i2}(\varepsilon_{i2}^{CCT})}}_{\substack{\text{CCT}\\ \text{early}\\ \text{childhood}}})^{\phi} + \eta_3(\underbrace{\overset{+}{I_{i3}(\varepsilon_{i3}^{CCT})}}_{\substack{\text{CCT}\\ \text{late}\\ \text{childhood}}})^{\phi}]^{\frac{1}{\phi}}, x_i), \qquad (10)$$

where $h_i = \theta_{i,t+4}$ denotes the individual long-term outcome and $\frac{1}{1-\phi}$ is the elasticity of substitution of investments made at different stages of childhood, with $\phi \in (-\infty, 1]$ and $\eta \geq 0$, and it is assumed that $\frac{\partial I_{it}}{\partial \varepsilon_{it}^{j}} \geq 0$ and $\frac{\partial I_{it}}{\partial \varepsilon_{is}^{j}} = 0$ for $t \neq s$ and $j \in \{WeatherShock, CCT\}$. We now analyze the empirical results of the paper through the lens of this framework.

Empirical results and theoretical framework. Empirically, our main effects of the weather shock and the CCT-induced investments on the outcome show that:

i. Weather shock exposure deteriorates children's outcomes, $\frac{\partial h_i}{\partial \varepsilon_{i1}^{WeatherShock}} < 0$;

ii. Receiving the CCT-induced benefit early in life improve children's outcomes, $\frac{\partial h_i}{\partial \varepsilon_{i2}^{CCT}} > 0$;

iii. Receiving the CCT-induced benefit relatively late in life has a weak effect on children's outcomes, $\frac{\partial h_i}{\partial \varepsilon_{i3}^{CCT}} \to 0$.

We want to show that, if we discipline the parameters of the theoretical model to match our empirical results (i)-(iii), the theoretical model would deliver additional predictions on interactions between the weather shock and the investment in the different periods consistent with our empirical results. We proceed in two steps. First, we show the necessary and sufficient conditions for the model to predict (i)-(iii):

Lemma 1. Equation (10) that describes the formation of human capital would predict (i)-(iii) if and only if:

1. $\eta_1, \eta_2 > 0$, $\frac{\partial I_{i1}}{\partial \varepsilon_{i1}^{WeatherShock}} < 0$, $\frac{\partial I_{i2}}{\partial \varepsilon_{i2}^{CCT}} > 0$, and

2. $\eta_3 \to 0$ or $\frac{\partial I_{i3}}{\partial \varepsilon_{i3}^{CCT}} \to 0$.

Proof. Using equations (9) and (10), the effect of a shock ε_{it}^{j} on individual i's human capital is given by $\frac{\partial h_i}{\partial \varepsilon_{it}^{j}} = \eta_t h_i^{1-\phi} I_{it}^{\phi-1} \frac{\partial I_{it}}{\partial \varepsilon_{it}^{j}}$. It follows that: a) $\frac{\partial h_i}{\partial \varepsilon_{i1}^{WeatherShock}} < 0$ if and only if $\eta_1 > 0$ and $\frac{\partial I_{i1}}{\partial \varepsilon_{i1}^{WeatherShock}} < 0$; b) $\frac{\partial h_i}{\partial \varepsilon_{i2}^{CCT}} > 0$ if and only if $\eta_2 > 0$ and $\frac{\partial I_{i2}}{\partial \varepsilon_{i2}^{CCT}} > 0$; and c), $\frac{\partial h_i}{\partial \varepsilon_{i3}^{CCT}} \to 0$ if and only if $\eta_3 \to 0$ or $\frac{\partial I_{i3}}{\partial \varepsilon_{i3}^{CCT}} \to 0$. $\square$

[51] To arrive to equation (10), begin by assuming that $f_t(\theta, I, x) = [\gamma_t^{\theta}\theta^{\phi} + \gamma_t^{I} I^{\phi} + \gamma_t^{x} x^{\phi}]^{\frac{1}{\phi}}$. Substituting backwards we obtain:

$$\theta_4 = [\gamma_3^{\theta}\gamma_2^{\theta}\gamma_1^{\theta}(\theta_1)^{\phi} + \gamma_3^{\theta}\gamma_2^{\theta}\gamma_1^{I}(I_1)^{\phi} + \gamma_3^{\theta}\gamma_2^{\theta}\gamma_1^{x}(x)^{\phi} + \gamma_3^{\theta}\gamma_2^{I}(I_2)^{\phi} + \gamma_3^{\theta}\gamma_2^{x}(x)^{\phi} + \gamma_3^{I}(I_3)^{\phi} + \gamma_3^{x}(x)^{\phi}]^{\frac{1}{\theta}}, \qquad (8)$$

Equation (8) corresponds to equation (10) for:

$$m(\theta, I, x) \equiv [\gamma_3^{\theta}\gamma_2^{\theta}\gamma^{\theta}(\theta_1)^{\phi} + I^{\phi} + \gamma_3^{\theta}\gamma_2^{\theta}\gamma^{x}(x)^{\phi} + \gamma_3^{\theta}\gamma_2^{x}(x)^{\phi} + \gamma_3^{x}(x)^{\phi}]^{\frac{1}{\theta}}. \qquad (9)$$

where $I \equiv [\eta_1(I_1)^{\phi} + \eta_2(I_2)^{\phi} + \eta_3(I_3)^{\phi}]^{1/\phi}$, $\eta_1 \equiv \gamma_3^{\theta}\gamma_2^{\theta}\gamma_1^{I}$, $\eta_2 \equiv \gamma_3^{\theta}\gamma_2^{I}$, and $\eta_3 \equiv \gamma_3^{I}$.

This lemma implies that, the empirical results on the main effects of the weather shock and the CCT-induced investments on the outcome can be rationalized in the theoretical framework if the early-stages ($t \in \{1, 2\}$) are "critical periods" (as defined above) and $\eta_1 > 0$, $\eta_2 > 0$ but $\eta_3 \to 0$; and/or health is a "critical investment" in the sense that $\frac{\partial I_2}{\partial \varepsilon_{i2}^{CCT}} > 0$ but $\frac{\partial I_3}{\partial \varepsilon_{i3}^{CCT}} \to 0$.[52]

Second, we show the implications of these conditions for the interactions between negative early-life shocks and subsequent investments in different periods:

Proposition 1. Under the conditions of lemma 1 and if $\phi < 1$, the human capital formation equation (10) predicts that $\frac{\partial^2 h_i}{\partial \varepsilon_{i1}^{WeatherShocks} \partial \varepsilon_{i2}^{CCT}} < 0$ and $\frac{\partial^2 h_i}{\partial \varepsilon_{i1}^{WeatherShocks} \partial \varepsilon_{i3}^{CCT}} \to 0$.

Proof. Using equations (9) and (10), the interactive effect of shocks ε_{it}^{j} ε_{is}^{r} on individual i's human capital is given by $\frac{\partial^2 h_i}{\partial \varepsilon_{it}^{j} \partial \varepsilon_{is}^{r}} = (1-\phi)\eta_t \eta_r h_i I_{it}^{\phi-1} I_{is}^{\phi-1} \frac{\partial I_{it}}{\partial \varepsilon_{it}^{j}} \frac{\partial I_{is}}{\partial \varepsilon_{is}^{r}}$. From condition (1) of lemma 1 it follows that if $\phi < 1$ then $\frac{\partial^2 h_i}{\partial \varepsilon_{i1}^{WeatherShock} \partial \varepsilon_{i2}^{CCT}} < 0$. From condition (2) of lemma 1 it follows that $\frac{\partial^2 h_i}{\partial \varepsilon_{i1}^{WeatherShock} \partial \varepsilon_{i3}^{CCT}} \to 0$. □

Proposition 1 implies that, given the empirical results on the main effects of the weather shock and the CCT-induced investments on the outcome, the theoretical framework would predict interactive effects between shocks in different periods aligned with our findings on dynamic complementarities. When the CCT-induced investment arrives in early childhood, its "main" effect is large since this is a critical period. But the CCT has a smaller effect on children who started with a lower stock of skills due to the weather shock ($\frac{\partial^2 h}{\partial \varepsilon_{i1}^{WeatherShock} \partial \varepsilon_{i2}^{CCT}} < 0$). In contrast, when the CCT-induced investment arrives later, both its "main" effect and its interactive effect with the weather shock is small ($\frac{\partial^2 h}{\partial \varepsilon_{i1}^{WeatherShock} \partial \varepsilon_{i3}^{CCT}} \to 0$). In sum, our results are not only consistent with leading theories on human capital formation but shed new light on complementarities by providing evidence that the timing and type (and duration) of investments matter.

We acknowledge that our empirical approach estimates reduced-form effects and it is not directly testing for the parameters of the production function itself as we do not have measures of inputs and outputs across the life-cycle.

[52] Note that the health investment is only available to eligible families with young children below age 7 (associated in the theoretical model with ε_{i2}^{CCT}), whereas the education investment is only available to eligible children 7+ (associated in the model with ε_{i3}^{CCT}).