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

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Abstract

We explore 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 reduce children's initial skills and ii), the introduction of conditional cash transfers (CCT) that promote investments in children's health and education. We show that the timing and type of CCT-induced investments matter for both the effects of CCTs and their interactive effects with weather shocks. When the CCT-induced investments occur in sensitive periods of human capital formation (e.g., early childhood), the effects are large and their interactive effects with weather conditions suggest that the returns of the program are even larger for children exposed to "normal" weather conditions. In contrast, CCT-induced investments that come relatively late in childhood (e.g., adolescence), have a smaller "main" effect and a smaller or zero interactive effect with weather shocks. We also find that initial CCT-induced health investments tend to have larger returns than initial CCT-induced educational investments. These findings shed new light on the developmental production function for human capital and the role of social policies in closing gaps generated by early-life adversities.

Keywords: Early-life influences, Human development, Social programs

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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 of the in-utero and early-childhood environment (Almond et al., 2017; Barker, 1990; Bleakley, 2010; Cunha and Heckman, 2007). However, children are exposed to a myriad of shocks and receive multiple investments from parents and government in different stages in their lives, so a key question that arises is: How do shocks and investments interact with each other to affect children's human capital?

In this paper, we study how human capital investments on children over different developmental stages, affect their long-term outcomes and how these investments interact with each other to influence their human capital. Providing evidence on interactions between investments is challenging. As discussed by Almond and Mazumder (2013), investments in children can be endogenously determined with children's endowments or with parental unobserved factors. Hence, to arguably estimate causal impacts on interactions, a researcher would need at least two sources of exogenous variation inducing changes in children's skills in different stages of development. Few empirical studies have estimated these interactions, possibly due to the difficulty it implies.

We fill this gap by constructing such a research design using data from Colombia, and by focusing on two policy-relevant events that affect millions of families across the world: i) the occurrence of adverse weather shocks – i.e., floods and droughts that significantly reduce children's initial skills– and ii), the introduction of social programs – i.e., conditional cash transfers (CCT) that provide monetary subsidies to families with young children conditional on investments in children's health and education. In particular, we provide empirical evidence on how CCTs, received at different stages in a child's life, affect his long-term educational outcomes, and how these effects interact with children's exposure to adverse weather shocks in their first years of life. We show that both the timing and type of CCT-induced investments matter for both the "main effects" of CCTs as well as for their interactive effects with the weather shocks. Our empirical results are consistent with theoretical models on human-capital formation predicting that: i) *timing and type* of investments matter (Attanasio et al., 2015; Carneiro et al., 2015; Heckman, 2008) and ii), investments in children at a given period may make subsequent investments more productive, also known as *dynamic complementarities* (Attanasio et al., 2017; Cunha and Heckman, 2007; Cunha et al., 2010; Heckman and Mosso, 2014).

The first shock to human-capital formation comes from early-life exposure to the weather shocks *El Niño* and *La Niña* of the 1990s. During these events, the normal patterns of tropical precipitation and atmospheric circulation are disrupted, triggering extreme climate events around the globe such as droughts, floods, or hurricanes. Exposure to extreme weather shocks has been shown to negatively affect children's health and cognitive outcomes through a number of mechanisms that include maternal stress, nutritional changes, infectious diseases, declines in agriculture, or disruptions to the economic activity (Aguilar and Vicarelli, 2012; Akresh et al., 2012; Baez et al., 2010; Dell et al., 2014; Kovats et al., 2003; Rocha and Soares, 2015; Rojas et al., 2014; Rosales-Rueda, 2016).

The second shock to human-capital investments is the introduction of *Familias en Acción*, Colombia's CCT program, which was rolled-out in the early 2000s, hence serving to our identification in terms of the chronological timing of shocks and investments. CCTs are assistance programs currently operating in 64 low- and middle-income countries, benefiting hundreds of millions of families, with the aim of fostering the accumulation of human capital among disadvantaged children through conditioning transfers on investments in children's health and education, and alleviating current household poverty.[1] The evidence shows that CCTs have successfully raised children's schooling, reduced, in some cases, the incidence of low child height and child mortality, and improved school progression (Baird et al., 2014; Fiszbein and Schady, 2009; García and Saavedra, 2017; Molina-Millan et al., 2016).

Our study leverages data from multiple administrative sources. In particular, 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 (or SISBEN), and the universe of CCT beneficiaries. 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 individuals born in Colombia in the 1990s. We then merge these individual micro data with information on rainfall at the municipality-month-year levels since 1980. Our outcomes of interest include both measures of educational attainment and achievement test scores in national exams that broadly capture changes in health, cognitive and noncognitive skill formation, which may have been affected by the exposure to weather shocks and the CCTs. In particular, we focus on: i) school drop-out, ii) high school graduation, and iii) ICFES test score, an exam that all high school graduates take regardless of whether they intend to apply to college.

Providing evidence on the interaction between weather shocks and CCTs requires that we credibly identify the individual impact of each of these "treatments" on the outcomes. To estimate the effects of exposure to weather shocks, we exploit the temporal and geographic variation in extreme precipitation at the month-year-municipality level in Colombia, during the main three weather events of the 1990s: *El Niño* droughts of 1991–1992 and 1997–1998

[1] While in 1997 there were only two CCT programs, this number rapidly increased to more than 60 in 2015. In Latin America alone, 26 CCTs currently serve 135 million people (Honorati et al., 2015).

and *La Niña* floods of 1998–2000 (see Figures 1 and 3 for the spatial and temporal variation of these shocks). Our preferred difference-in-difference (DD) specification compares the outcomes of children born in the same municipality but in different months and years, and therefore exposed to varying levels of extreme rainfall (i.e., floods or droughts) during *El Niño* and *La Niña* episodes. We show that *not* being exposed to these adverse weather shocks from in utero to age 3 (which could be considered as a positive early-life investment) improves children's education in the long-term. Our estimates show, on average, a 5.0% increase in the probability that a child does *not* drop out from school (with respect to the outcome mean), a 7.1% increase in the probability of completing high school (with respect to the outcome mean), and a 0.05 standard-deviation (*SD*) increase in the ICFES test score. In terms of potential mechanisms, we find that *no* exposure to *El Niño* and *La Niña*: i) increases household income but this effect tends to dissipate after three years; and ii), increases household food consumption (and in particular the consumption of grains, fruits, and vegetables). Using the Demography and Health Survey data we found that *no* weather shock exposure is associated with a significant decline in the probability of low birth weight, with an increase in breastfeeding duration, and an increase in height-for-age, both in the medium- and long-term. These findings suggest that child's health and nutritional status are relevant pathways through which these early-life shocks operate to affect children's long-run educational outcomes. Furthermore, our estimates of the effects of weather shocks do not seem to be explained by potential sources of selection bias such as migration, fertility, or mortality.

To provide evidence on the effects of CCTs on child outcomes, we exploit the eligibility rule for *Familias en Acción* given by the SISBEN poverty index score, to estimate a regression-discontinuity (RD) design. Our RD design strategy allows us to compare children in families on both sides of the cutoff that are similar in all their observable characteristics (including their likelihood of experiencing early-life shocks) except for their eligibility to the program. Using this RD framework, we find that actual program participation increases the probability that a child remains enrolled in school by 10%, as well as increases high school graduation and the ICFES test exam score by 30% and 0.13 SD, respectively. Of note is that the effects on school retention are measured years after the child is enrolled in the CCT program and hence, do not reflect the pure conditionality of the cash transfer[2] but rather suggest that the program has a long-term impact on school retention as well as on the other outcomes. Some evidence on potential mechanisms of the CCT suggests that the CCT benefit is associated with children being enrolled in higher quality public schools (as measured

[2]For instance, school-aged children are required to attend at least 80% of school classes per academic year in order to be eligible for the program (in addition to meet the poverty threshold requirement).

by the average ICFES score of the school) and with a lower rate of child labor, which could be consistent with the idea that the transfer may help alleviate household budget constraints or with the fact that CCT beneficiaries may learn of better ways to maximize their child's potential through their participation in the program (e.g., by selecting into better schools).

Since *Familias en Acción* conditions cash transfers for families with young children based on health investments and for those with older children based on educational investments, we then examine whether differences in the timing (and the type) of CCT-induced investments matter, following previous research that shows that early childhood is a critical period for development (Almond et al., 2017; Heckman and Mosso, 2014). Rather than focusing on the age at which a child was first enrolled in *Familias en Acción* (which is an endogenous decision from a family's perspective), we exploit the timing in the rollout of the program (see Figure 2), and focus on the age at which the CCT arrived at a child's municipality. We find that the return of the CCT-induced investments declines with the age at which children receive the benefit. Children who received the CCT-induced investments in early childhood (ages 0 to 6) were 12% more likely to remain enrolled in school, while those who received it later experienced a small and statistically insignificant increase. Moreover, we are able to provide evidence that both timing of exposure to the program and type of investment matter: comparing children within the same age range at the time of CCT rollout and who were exposed for a similar period to the program, we found that children who were slightly younger at the time of CCT rollout and who were therefore initially eligible to receive CCT-induced health-investments, experienced a 9% higher probability on school retention than children who were slightly older at CCT rollout and who were therefore only eligible to receive CCT-induced educational-investments.

To explore the relationship between weather shocks and CCTs, we then combine both sources of variation into a DD-RD design (see Figure 3). This framework allows us to test if the CCT had a differential impact on children who started with a higher stock of initial skills due to *no* exposure to the *El Niño* and *La Niña* weather shocks. We first provide evidence that experiencing the weather shock does not affect a household's eligibility or take-up of *Familias en Acción*. Then, we show that, on average, there is little evidence that the CCT-induced investments have a significant interactive effect with the weather shock. However, when we examine differences in the timing of exposure to the CCT by child's age at rollout, we find that for children who received the cash transfer in early childhood, the returns of the CCT-induced investment tend to be higher for weather-unaffected children than for those exposed to floods or droughts. Although this result suggests that the return of the CCT is larger for better-off children, we still find that the "main" effect of the CCT is strictly larger (and positive) than the negative effect of the weather shock. Thus, from a policy perspective we could say that CCT programs play a key role in mitigating early-life shocks experienced by low-income children. While the evidence on children who receive the CCT at later ages also goes in the direction of a dynamic complementarity, the interactive effect with the weather conditions is much weaker, which is likely due to the fact that the CCT-induced investments are less effective on these children to begin with.

Contribution and related literature. Our study relates to three bodies of work. First, few empirical studies have causally estimated interactions between investments and the evidence is so far mixed: some have found little evidence that shocks and investments interact to affect later outcomes (Aguilar and Vicarelli, 2012; Malamud et al., 2016); others have shown results that may be consistent with dynamic complementarities between multiple investments (Gilraine, 2017; Johnson and Jackson, 2017); and others, in contrast, have found evidence on substitution (Rossin-Slater and Wüst, 2015) or mitigation—i.e., that investments may actually have larger returns on those exposed to adverse shocks (Adhvaryu et al., 2015; Gunnsteinsson et al., 2014; Sviatschi, 2018).[3] We contribute to this literature by being the first study to empirically show that interaction effects depend on the developmental stage at which the investments occur, as well as the nature of these investments. In particular, our findings suggest that complementarities can be detected when the second investment occurs early in life, while weaker effects are found when this second investment arrives at later ages. Also, we show that different types of investments lead to different interactive effects. In that sense, our paper helps reconcile some of the conflicting results in the literature.

The second body of work related to this paper is the extensive research on the effects of CCTs on human capital. The evidence shows that CCTs have successfully raised children's schooling, improved child's nutrition, promoted child vaccinations and health care visits, and increased household consumption (Baird et al., 2014; Fiszbein and Schady, 2009; Molina-Millan et al., 2016). However, little research has examined the efficacy of these programs on students' learning outcomes (García and Saavedra, 2017; Molina-Millan et al., 2016).[4] We contribute to this growing literature in two ways. First, we show novel evidence on the potential sustained impacts of these programs on students' achievement test scores at age 18 and on the potential for mitigation of CCTs in alleviating exogenous early-life shocks. Considering that more than 60 low- and middle-income countries (including the U.S. and the U.K.) currently operate a CCT and that their costs represent a large component of

[3] Other set of studies have also found differences in the returns of positive investments in early-life by subgroups (e.g. Bhalotra and Venkataramani, 2015; Havnes and Mogstad, 2015), and by initial human capital endowments (Aizer and Cunha, 2012; García and Gallegos, 2017).

[4] One exception is the study by Barrera-Osorio et al. (2017) that provides novel evidence on the effects of CCTs on tertiary education and on the importance of payment schemes through which transfers are delivered.

the social safety net budget in these countries[5], learning about their potential direct and indirect impacts is imperative. Second, we examine one possible mechanism through which student-learning gains operate, which is that CCTs help students enroll into better schools.

Our paper is also related to a third strand of research: the effects of weather conditions on human capital. While some studies have shown that childhood exposure to small or moderate increases in rainfall is associated with better economic and health outcomes (Maccini and Yang, 2009; Shah and Steinberg, 2017), others have shown that exposure to extreme weather events is detrimental for human capital (Aguilar and Vicarelli, 2012; Akresh et al., 2012; Baez et al., 2010; Pathania, 2007; Rocha and Soares, 2015; Rosales-Rueda, 2016). To our knowledge, few studies have documented the long-run impacts of extreme weather events (Dinkelman, 2017). We contribute to this literature by estimating the effects of floods and droughts during *El Niño* and *La Niña* events, from in-utero up to age 3, on high school graduation and on achievement-test scores measured at age 18 using the universe of students in Colombian public schools.

This paper is structured as follows. The next section describes the background for the empirical strategy: the 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 discusses the results through the lens of a human capital formation model. Section 7 provides evidence on potential mechanisms, and Section 8 explores some selection concerns and robustness checks. Lastly, Section 9 concludes.

2 Background for the Empirical Strategy

2.1 Weather Shocks in Developing Countries

The first shock to human-capital formation that we exploit is the occurrence of *El Niño* and *La Niña* weather events in Colombia during the 1990s. Weather shocks (and other natural disasters) are perhaps the most adverse conditions faced by households in developing countries (Dell et al., 2012; Fay et al., 2015; Hsiang and Jina, 2014), and children bear a sizable portion of the adverse effects of these disasters (Akresh, 2016; Currie and Vogl, 2013; Hanna and Oliva, 2016).

***El Niño* and *La Niña* Events.** *El Niño Southern Oscillation (ENSO)* is a complex phenomenon of changes in ocean temperatures in the equatorial Pacific that disrupts normal

[5]For instance, the budget of Mexico's CCT Progresa in 2010 represented about half of 1 percentage point of the country's GDP .

weather patterns, bringing heavy rains, hurricanes, and droughts to different parts of the globe. Studies have shown that nearly 25% of the world's land surface experiences a change in the probability of high or low precipitation due to ENSO, of which the majority is located in the tropics (Zebiak et al., 2015).

El Niño and *La Niña* are the opposite phases of ENSO. While El Niño is characterized by unusually high ocean temperatures, *La Niña* is associated with unusually low ones.[6] *El Niño* and *La Niña* events manifest in different ways across geographic regions. *El Niño*, for instance, produces droughts in the northern part of South America, from Colombia to northern Brazil,[7] whereas it causes floods and landslides in the southern South America.[8] *La Niña*, in contrast, produces the opposite pattern in these countries—e.g., in Colombia, it manifests in the form of intense floods. The cycles of these events also vary substantially. While *El Niño* and *La Niña* are recurrent events that tend to repeat every two to seven years, and which usually last between nine months and two years, random changes in atmospheric conditions may dampen or amplify their strength, thus making their intensity and duration hard to predict (Climate Prediction Center, 2005; Kovats et al., 2003; Wittenberg et al., 2014).

In this paper, we focus on the ENSO events that took place in the decade of the 1990s: The two *El Niño* episodes of 1991–1992 and 1997–1998 and *La Niña* of 1998–2000. Figure 1 illustrates the temporal and geographic variation in extreme precipitation during each of these events across municipalities in Colombia. In particular, the figure shows the duration of weather shocks measured by 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.[9] The first two maps refer to the *El Niño* events—which manifest in droughts or extremely low precipitation levels—and the third map illustrates the *La Niña* event—which manifests in floods or extremely high precipitation levels. As the figure illustrates, even within the same decade, the geographic and temporal variation in rainfall was substantial across the territory.

The first shock, the 1991–1992 *El Niño* drought, was considered a "strong" episode

[6] *El Niño* was first known in the 1500s by Peruvian farmers and fishermen who noted that high seawater temperatures were associated with increased rainfall and with a reduction in the anchovy catch. Because this phenomenon occurred after Christmas, when the Christ Boy or *El Niño Dios* was born, they named this phenomenon *El Niño* (Zebiak et al., 2015).

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

[8] Peru, Ecuador, Bolivia, and Chile.

[9] 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)

according to both the Southern Oscillation Index (SOI)[10] and the Sea Surface Temperature (SST) index,[11] two indices that scientists have historically used to classify the intensity of ENSO events.[12] The 1991–1992 *El Niño* drought lasted 16 months (from April 1991 to July 1992) and led to significant economic losses in Colombia as well as in other affected regions of the world.[13] In Colombia, this *El Niño* caused frequent water shortages due to the extremely low levels of water accumulation in the hydroelectric dams and led to a 12-month period of daily electricity rationing in the whole country. The agricultural sector was largely affected: Cotton, sorghum, and potato crops experienced productivity losses of 70%, 35%, and 20%, respectively (Carvajal et al., 1999), which contributed to an 8% increase in the prices of food from 1991 to 1992 (Avella, 2001).

The second weather shock, the *El Niño* 1997–1998 drought, was regarded as a "super Niño," one of the most powerful ENSOs in recorded history. It caused an estimated 16% of the world's reef systems to die and a temporary increase in global air temperature of 1.5 °C, compared to the usual increase of 0.25 °C associated with a typical *El Niño* event (Trenberth et al., 2002). In Colombia, this *El Niño* was considered one of the most intense *El Niño* episodes of the 20th century, which led to historically high temperatures, as well as frequent forest fires and severe droughts, affecting 90% of Colombian municipalities (Instituto de Hidrología, Meteorología y Estudios Ambientales, 2002).[14] The total direct and indirect socioeconomic losses represented 1% of the GDP, which were disproportionately concentrated in the agriculture, electricity, and water supply industries (Cadena et al., 2006; Campos et al., 2012; Corporación Andina de Fomento, 1998). The total cultivated area decreased by 3%, mainly affecting the production of maize, sorghum, cotton, and milk. The destruction of crops and livestock contributed to significant food shortages and increases in local food prices—from 17% at the end of 1997 to almost 30% in the first quarter of 1998 (Avella, 2001).

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 experienced the highest temperatures and most intense droughts. The economic sectors most negatively

[10] A standardized index based on the observed sea level pressure differences between Tahiti and Darwin, Australia. See https://www.ncdc.noaa.gov/teleconnections/enso/indicators/soi/.

[11] An index that captures temperature anomalies in a certain region of the equatorial Pacific. See https://www.ncdc.noaa.gov/teleconnections/enso/indicators/sst.php.

[12] Bocanegra et al. (2000) compile SOI and SST for the case of Colombia's ENSO events since 1939.

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

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

impacted by the heavy rainfall were agriculture—with significant damage to coffee, sugar cane, and fruits—infrastructure, and healthcare services (International Federation of Red Cross and Red Crescent Societies, 2000).

According to the World Health Organization, ENSO's severe droughts and floods can lead to a wide range of health problems including malnutrition, disease outbreaks, heat stress, and respiratory diseases, and to increases in food insecurity through agricultural losses and infrastructure damage. In terms of disease outbreaks, Bouma et al. (1997) showed that malaria increased by 17.3% during the 1997–1998 *El Niño*, which was in part explained by the abundance of mosquitoes that contribute to its transmission. The incidence of dengue disease also increased during the 1997–1998 *El Niño*, going from 74 cases per 100,000 inhabitants before the event started to 192 in 1998 (Corporación Andina de Fomento, 1998). During the 1998–2000 *La Niña* floods, Colombia also faced an increase in the incidence cholera, leishmaniasis, and tuberculosis (Corporación Andina de Fomento, 1998; Departamento Nacional de Planeación, 2012).

2.2 Conditional Cash Transfer Programs

The second shock to human capital formation studied in this paper, is the introduction of Colombia's CCT program: *Familias en Acción*. Since the 1990s, more than 60 low- and middle-income countries have implemented CCTs with the dual aims of alleviating long-run poverty by fostering the accumulation of human capital among disadvantaged children and of reducing current poverty through regular transfer payments.

Familias en Acción. Modeled on Mexico's CCT program *Progresa*, *Familias en Acción* began in 2001 by providing conditional subsidies to approximately 600,000 poor families based on investments in their children's human capital.[15] The program has two components: (i) health and nutrition and (ii) education. Health and nutrition transfers are granted to mothers[16] with children below age 7 with the intention of supplementing households' food consumption. These transfers are conditional on fulfilling certain healthcare requirements such as child vaccinations and growth development checkups, as well as attendance at courses on nutrition, hygiene, and contraception by the child's mother. The amount of the monthly health subsidy is approximately US$15, which corresponds to 11% of the minimum monthly wage (m.m.w.) in 2000.[17] Education transfers (the largest component) provide grants to

[15]Colombia's population in 2001 was approximately 40 million.

[16]Subsidies are directly granted to the mother with the purpose of strengthening her role and bargaining power within the family and the community (Departamento Nacional De Planeación, 2005).

[17]Chronic malnutrition (height for age more than two standard deviations below average) in municipalities eligible for *Familias en Acción* in 2002 was 22% (Attanasio et al., 2012).

mothers with children between 7 and 17 years of age with the intention of supplementing household spending on children's education; these transfers are conditional on the child attending at least 80% of school classes per academic year. The amount of the monthly education grant varies by school grade: For families with children in primary school, the subsidy is US$6 (approximately 5% of the m.m.w.), whereas for those in secondary education, it is raised to US$12 (approximately 9% of the m.m.w.). While health and nutrition subsidies are paid on a monthly basis, education subsidies follow a bimonthly scheme and only cover ten months per year.[18] On average, families remained enrolled in the program for three years (i.e., the whole duration of the initial phase).

Phase I of *Familias en Acción* took place between 2001 and 2004 (see Figure 2), in which 622 municipalities (out of the 1,100) were selected to participate based on five criteria: less than 100,000 inhabitants, not a department capital, sufficient basic education and health infrastructure to absorb the new demand for social services, had a bank, and had municipality administrative agencies with relatively up-to-date welfare information to register new beneficiaries (Attanasio et al., 2010). This selection of municipalities included small to large villages and excluded large metropolitan and urbanized areas (i.e., Bogota, Medellin, etc.).

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 forcefully displaced families also became eligible with the program's expansion.[19] As *Familias en Acción* reached national coverage, the government introduced a maximum limit of five years for beneficiaries to be enrolled in the program. Today, *Familias en Acción* operates nationwide, serves around three million families, and by 2013 its budget represented approximately 0.8% of the national budget (Departamento Administrativo Para la Prosperidad Social, 2017).

Eligibility for *Familias en Acción*. Eligibility for the program is based on the poverty index score SISBEN –*Sistema de Identificación y Clasificación de Potenciales Beneficiarios* –, also known as the "Census of the poor", which covers 60% of Colombia's population.[20] The SISBEN represents the government's tool to identify impoverished populations in Colombia and therefore the mechanism through which social programs are targeted to specific groups.

[18]School enrollment at ages 7 to 17 in eligible municipalities for *Familias en Acción* in 2002 was 83.5% (Attanasio et al., 2012).

[19]Forced displacement has been one of the most dramatic consequences of the armed conflict in Colombia. The total displaced population in the country reached over 3.5 million since 1997, 8% of the total population (World Health Organization and United Nations High Commissioner for Refugees, 2013). Displaced groups tend to have very low socioeconomic indicators, including educational attainment and health status.

[20]The SISBEN includes 25 million individuals.

This index 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. The SISBEN ranges from 0 (poorest) to 100 (less poor). According to the SISBEN score, households are divided into six welfare-level groups, of which *Familias en Acción* targets those in the lowest level (SISBEN Level 1), while other social programs such as subsidized healthcare or retirement pensions, cover SISBEN Levels 1 and 2.Table 1 shows the SISBEN score cutoffs used to determine eligibility to the program (i.e., Level 1). Note that the thresholds vary by whether a household lives in the rural versus urban segment of the municipality. The fact that *Familias en Acción* only targets Level 1 while other programs target Levels 1 and 2, actually represents a strength of our identification strategy as there is no change in eligibility to other social programs that coincides with the discontinuity in eligibility for *Familias en Acción*.

3 Data

3.1 Administrative Data

The richness of the data is one of this study's major strengths. We use several sources of administrative records: the "universe of the poor" or SISBEN I, the universe of students in Colombia's public school system, the universe of ICFES exam test takers, and the universe of beneficiaries of *Familias en Acción*. We describe each of these datasets below.

The "Universe of the Poor": The SISBEN We use the first wave (cross-section) of SISBEN or Census of the Poor, collected in 1994–2003.[21] The SISBEN data include rich demographic and socioeconomic information of all household members including gender, age, exact date of birth, education, marital status, occupation, income, household size, dwelling characteristics, and location of the household, as well as the poverty index score. The data contain information on over 25 million individuals—the poorest Colombians, around 60% of the total population. The SISBEN allows us to identify both the eligible and the ineligible households for *Familias en Acción*, prior to the introduction of the program, based on their SISBEN score.

The Universe of Students in Colombia's Public Schools: R-166 The second source of data is the core database of the Ministry of Education, which provides information on

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

school progression for all students in public schools in Colombia.[22] 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.[23] Therefore, we use data that start in 2005 (the first year these records became available) up to 2015. In particular, the R-166 allows us to observe the first year a child entered the school system (e.g., first grade) up to high school graduation (or dropout) for everyone who was ever enrolled in the public school system in Colombia.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 that a child attends, for a sample of approximately 93 million student–year observations. A unique advantage of using the R-166, is that it includes the exact municipality of birth for each student, which is not available in any other administrative dataset.

End-of-High School Exam: The ICFES The ICFES is the national high school exit exam administered by the *Instituto Colombiano para el Fomento de la Educación Superior*. This mandatory exam is taken by high school seniors regardless of whether they intend to apply to college (although for those who enter college, the ICFES score does determine college and major entrance). It includes separate tests on math, Spanish, social studies, sciences, and an elective subject. We use information from all students who took this exam from 2004 to 2014 (approximately one million observations).

The System of Beneficiaries of *Familias en Acción* The last dataset we use is the system of beneficiaries of *Familias en Acción*, which is a longitudinal census of the universe of program participants. It includes detailed information such as demographic and socioeconomic characteristics of the recipient household, the amount transferred ($) to a family, the type of benefit (education or health) that a child receives, and the family's duration in the program (measured in months). We use data on the program's initial phase, which covers the period from 2001 to 2004, and which includes records on 2.8 million individuals (or 600,000 families) living in 622 municipalities (see Figure 2).

To link individuals across datasets, we use their individual identifiers such as full names (first and middle names and fathers' and mothers' maiden names), birth dates (day, month, year), and national ID numbers (type of document and number). Details on the matching process are provided in the Robustness Checks section.

[22] Approximately 93% of children in SISBEN Levels 1 and 2 attend a public school in Colombia.

[23] MinEducación (2017) offers more information on this resolution.

3.2 Rainfall Data

These data come from the Colombian Institute of Meteorology and Climate Conditions (IDEAM), which registers precipitation levels in each of the 1,100 municipalities in Colombia since 1980.[24] To identify rainfall shocks, we focus on *El Niño* (droughts) and *La Niña* (floods) events during the 1990s. 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. In other words, we consider both floods and droughts as being similarly detrimental shocks 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, 2017). The following equation describes the way how we construct the weather shocks:

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

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 the 80th percentiles of the municipality's monthly historical distribution since 1980, and $\mu(r_{jtm})$ is the rainfall distribution. We also examine other definitions of weather shocks such as one standard deviation cutoffs or use droughts and floods separately. We provide results on these alternative specifications in the Robustness Checks section. The rainfall dataset is then merged to the administrative records at the municipality–month–year level.

3.3 SISBEN Manipulation and Sample of Interest

SISBEN manipulation. A key identification assumption of the RD design is that individuals have imprecise control over their SISBEN score; in other words, individuals are randomly assigned around the cutoff.[25] Camacho and Conover (2011) showed that manipulation of the SISBEN score emerged in some municipalities as a result of the score algorithm being released to local officials and that this practice mainly occurred between SISBEN Levels 2 and 3, where the bundle of social benefits becomes more generous. The *Familias en Acción*-relevant cutoff is between Levels 1 and 2.

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

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

To asses the potential for manipulation in the running variable, we first examine the distribution of the SISBEN score in both urban and rural areas, as shown in Figure 4. A visual inspection provides little evidence of manipulation between Levels 1 and 2 in urban areas (Panel A), however, we do find a heap 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, 2016).[26] 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. Based on these findings, we perform all our analyses focusing on households living in the urban segment of the municipality. Doing so does not restrict any municipality in the sample, it mainly reduces the focus to households living in or close to the village center and excludes those in remote areas.

Sample of interest. We restrict our data to children who were born between 1988 and 2000 in Colombia, with information on their municipality of birth, whose families live in the urban segment of the municipality, and belong to SISBEN Level 1 (eligible to receive the CCT) or SISBEN Level 2 (ineligible). We focus on these cohorts because they were exposed to the *Familias en Acción* rollout early enough (i.e., previous cohorts were too old to receive the transfer) and because their early years coincided with the occurrence of *El Niño* and *La Niña* events of 1991–1992 (drought), 1997–1998 (drought), and 1998–2000 (floods).

3.4 Period of Exposure to Early-life Shocks

Following the literature in developmental psychology, epidemiology, and more recently in economics on sensitive periods for skill formation (Gluckman and Hanson, 2005; Heckman, 2008; Knudsen et al., 2006; Thompson and Nelson, 2001), we focus on specific periods of children's early life, which we defined as the in-utero period (nine months before birth) and the early years (ages 0–3). We use both the date of birth and the municipality of birth to identify these stages. For example, in-utero exposure is determined by counting backwards nine months from a child's month of birth in the municipality of birth. Exposure in the early years would cover the first three years of life (starting in the month after birth +36 months). Exposure to weather shocks refers to the number of months within these developmental stages –i.e., from in-utero up to age 3 – that a child's municipality of birth

[26] 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).

monthly precipitation is above the 80th or below the 20th percentile of the municipality's monthly historical distribution since 1980.

3.5 Outcome Variables

There are three the outcomes of interest:

1. ***Not* a school dropout:** 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).[27] The mean of this outcome is 57% (Table C.1). This outcome is measured for everyone in the sample (years of birth: 1988–2000).

2. **High school graduation:** This dummy variable takes the value of one when an individual has completed high school and zero otherwise, conditional on having been enrolled in middle school. Forty-two percent of students graduate from high school in our sample of children in SISBEN Levels 1 and 2 (Table C.1). This outcome is measured for the "older" cohorts in the sample (years of birth: 1988–1995).

3. **ICFES 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 (Table C.1). This outcome is measured for the "older" cohorts in the sample (years of birth: 1988–1995).

The sample of interest varies by outcome. In the case of "*Not* a school dropout", the sample includes 259,347 students born in Colombia from 1988 to 2000, while the ICFES sample includes 102,987 students who born between 1988 and 1995 The high school sample is analogous to the ICFES sample and includes 131,509 individuals.

3.6 Descriptive Statistics

Table C.1 shows summary statistics on all children born between 1988 and 2000, whose families are either eligible (SISBEN Level 1) or ineligible (SISBEN Level 2) to receive *Familias en Acción*. Overall, we find that children in SISBEN Levels 1 and 2 come from disadvantaged households. Ninety one percent live in households where the head has primary education or less and only 29% come from families where the parents are married. Households tend to

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

have on average six to seven members. Column 2 shows that families around the cutoff[28] are fairly similar to those in the full sample of eligible and ineligible families.

Regarding exposure to 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. On average, these children were exposed to 1- and 7-months of shocks while in-utero and during the early years, respectively.

4 Methods

To examine the interactions between early-life conditions and subsequent human capital investments, we conduct our empirical analysis in three steps. First, we copare the outcomes of children born in different municipalities and in different years and months, and were therefore differentially exposed to the weather shock in their first years of life. To facilitate the reader's interpretation, we define exposure to weather conditions as "*Not* exposed to the adverse weather shocks", which could be considered as a positive early-life investment –i.e., in the sense that small or moderate changes in rainfall vs. extreme events have positive effects on child outcomes. Second, we use a RD design to estimate the effects of the Colombian CCT program on children's education. Third, we combine these two sources of variation to estimate the interactive effects between *No* early-life weather shocks and subsequent human-capital investments induced by the conditionality of the program.

4.1 Effects of Early-life Shocks on Human Capital

We estimate the effects of *not* being exposed to weather shocks in early-life using a difference-in-difference specification:

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

where Y_{ijtm} is the outcome of child i who is born in municipality j, in year t, and in month m. $NoWeatherShock_{jtm}$ represents the number of months that a child was *not* exposed to extreme weather shocks during *El Niño* events of 1991–1992 and 1997–1998 and *La Niña* event of 1998–2000 from in-utero through age 3 depending on his/her municipality, month, and year of birth. Thus, δ_k captures the marginal effect per one month of "normal" weather conditions. $\mathbf{X_i}$ is a matrix that includes sociodemographic characteristics of a child and

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

family such as the child's gender, age, and baseline school grade[29]; the mother's age, education, and marital status; household size; access to water and sewage; and year of SISBEN interview fixed effects.[30] The terms $\alpha_j, \alpha_t, \alpha_m$ denote fixed effects for municipality, year, and month of child's birth that help capture time-invariant municipality-level characteristics, seasonality of conceptions, and shocks that are common to all children born in a given year and month. Lastly, ϵ represents the random error term. To address potential spatial and time correlation, we cluster standard errors at the municipality level.[31]

The main identifying assumption required to consistently estimate the effects of changes in weather conditions on children's outcomes is the independence between the error term ϵ and the *NoWeatherShock*, after controlling for geographic and temporal fixed effects. While we cannot directly test for all potential omitted variables, we assess the degree to which variation in weather exposure in early in life is correlated with a child or family's sociodemographic characteristics. Results in Table 2 show little evidence that families of certain observable attributes may be more likely *not* to experience the events of *El Niño* and *La Niña*, providing support for our identification strategy.

4.2 Effects of Investments on Human Capital

Next, we estimate the effects of CCTs on children's educational outcomes. Figure 5 shows program participation by SISBEN score.[32] We find that (i) the jump in the probability of participating in the program is 30 percentage points around the cutoff; (ii) among those who are eligible, between 52% and 65% participate in the CCT; and (iii) among those who are not eligible to receive the CCT, between 3 and 20% actually receive the cash transfer. Given this imperfect compliance, we use a fuzzy RD design (instead of a sharp design) that exploits the SISBEN assignment rule as an instrument for CCT participation.[33] Equation 3 describes the first stage:

$$CCT_{ijtm} = \pi_0 + \omega T_i + \lambda g(S_i - c) + \beta \mathbf{X_i} + \alpha_\mathbf{j} + \alpha_\mathbf{t} + \alpha_\mathbf{m} + \upsilon_\mathbf{ijtm}, \tag{3}$$

where CCT_{ijtm} represents CCT participation: This indicator takes the value of one if child i who is born in municipality j, in year t, and in month m participated in the program. T_i denotes if a child i is eligible to participate based on whether his/her family SISBEN

[29]Baseline refers to the first year that a child is observed in the administrative data, R-166.

[30]Information on race/ethnicity is unavailable in the SISBEN data.

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

[32]The cutoff SISBEN score for Level 1 has been normalized to 0.

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

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 SISBEN score relative to the cutoff. We perform local linear regressions and to determine the optimal bandwidth, we employ the bandwidth selector procedure proposed by Imbens and Kalyanaraman (2012), which suggested an optimal bandwidth of three points below and above the poverty index cutoff.[34]

Lastly, Equation 4 describes the second stage regression:

$$Y_{ijtm} = \beta_0 + \gamma \widehat{CCT}_{ijtm} + \varphi f(S_i - c) + \beta \mathbf{X_i} + \alpha_\mathbf{j} + \alpha_\mathbf{t} + \alpha_\mathbf{m} + \varepsilon_\mathbf{ijtm}, \tag{4}$$

where γ is the coefficient of interest that captures the causal local average treatment effect of receiving the CCT on children's educational outcomes. This model includes the same covariates as in 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. We plot the distribution of household characteristics by SISBEN score around the CCT cutoff (depicted by a solid vertical line). We find that households around the cutoff are similar in terms of household head's age, education, marital status, access to water or sewage, and household size as shown in Figure 6.[35]

4.3 Interaction between Early-Life Shocks and Investments

Finally, to explore potential interactive effects between shocks and investments, we combine both sources of variation into a difference-in-difference with a RD framework. Equation 5 describes this model.

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

where δ measures the impact of *not* being exposed to weather shocks in the early stages for children who did not receive the CCT and γ measures the effect of the CCT for those who

[34]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 SISBEN score is discrete), we show results for a range of bandwidths around the optimal bandwidth (i.e., two and four SISBEN points around the cutoff), which we show in Appendix B.

[35]Similar results of no correlation between family characteristics and CCT cutoff, are found in a regression context that accounts for geographic and temporal fixed effects.

suffered from early-life adverse weather shocks. The parameter of interest, τ, captures the differential effect of the CCT for those who experienced "normal" weather conditions from in-utero to age 3.

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 eligibility cutoff. To address this concern, we check whether the probability of being eligible to the CCT, the distance to the SISBEN cutoff, or the take-up of the program is associated with weather conditions from conception up to age 3. Table 3 shows that children who were *not* affected by floods or droughts in their first years of life, are not more or less likely to be eligible to the CCT, participate in the program, or have a lower poverty index score.

5 Results

5.1 The Effects of Weather Conditions on Human Capital

Table 4 presents the estimates of weather conditions on children's outcomes. We show the effects for the full sample (children in SISBEN Levels 1 and 2) as well as for those in the optimal bandwidth sample of the RD design (three points above and below the cutoff to *Familias en Acción*). Again, we define exposure to weather conditions as "*not* exposed to the adverse weather shocks", which could be considered as a positive early-life investment –i.e., in the sense that small or moderate changes in rainfall vs. extreme events have positive effects on child outcomes. Overall, we find that *not* being exposed to adverse weather during *El Niño* and *La Niña* events has a positive impact on children's education, which suggests that these shocks represent a substantial source of long-term disadvantage. A child *not* exposed to the average 8-month duration of adverse weather shocks, experiences a 5.0% increase in the probability of *not* dropping out from school (with respect to the outcome mean), a 7.1% increase in the probability of high school completion (with respect to the outcome mean), and a 0.05 SD increase in the score of the ICFES exam (with respect to the outcome's standard deviation).[36]

We also estimate the effects of weather shocks using alternative definitions such as including other thresholds of rainfall shock exposure, separating the shocks between droughts and floods, or using different cutoffs (e.g., a one standard deviation instead of the upper 80th percentile). These results are shown in Appendix Section B.2 and suggest that our find-

[36]The estimates of the effects of weather shocks on the sample of rural households are consistent to those that we find in the urban sample. For instance, we find that exposure to "normal" weather conditions increases the probability that a child does not drop out of school by 5.4% or increases the ICFES score 0.06 SD.

ings are robust to using alternative specifications. Also, as our definition of weather shocks groups together floods and droughts, in Appendix Section B.2 we show that the effects are remarkably symmetric. Separating between floods and droughts in the main specification, we find that the point estimate of the impact of *no* droughts exposure on school retention is 0.0039, statistically significant at the 5% level, whereas that of *no* floods exposure is 0.0029, statistically significant at the 1% level.

While a related literature has shown that moderate increases in rainfall are associated with better long-term outcomes (Maccini and Yang, 2009; Shah and Steinberg, 2017), 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), which 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 extreme shocks more broadly, we also find that 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 6.3% decline in high school completion and a 0.10 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 with developing country) were 20% less likely to attend school.

5.2 The Effects of CCTs on Human Capital

In this section we show how human-capital investments induced by the CCT affected children's education. Since the decision to enroll in the program is endogenous, we first instrument CCT participation using the fuzzy RD approach described in Section 4. Results on the first stage are presented in Appendix Table C.2 and they show that: (i) there is a strong relationship between eligibility and participation and (ii), being eligible for CCTs increases participation by 30 percentage points (pp).

The first column in Tables 5, 6, and 7 present the estimates of receiving CCTs on children's education across the different outcomes. Our findings show that, children who receive investments as a result of the CCT, experience an increase in: school retention of 9.5% (as shown in Table 5), in high school completion of 30% (Table 6), and in the ICFES score of 0.13 SD (Table 7).

These 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 3.6pp) and increase high school graduation by 3.3pp (we find an ITT estimate of 3.7pp). 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., 2013), 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 absence of the program would have dropped-out of school, the marginal student affected by the program may actually be different (e.g., have a lower ability) to other students. Hence, finding a positive and significant effect on both high school and ICFES test score suggests that, CCTs could actually improve students' learning. In that sense, our results on both outcomes and specially that on academic achievement, provide novel evidence to the body of research on CCTs.

5.3 The Interaction Between Weather Conditions and CCTs

After showing the independent effects of weather and CCTs on education, we now estimate potential interactive effects between both treatments. Columns 2 and 3 in Tables 5, 6, and 7 display these results. To facilitate the interpretation of our estimates, we present some calculations in the bottom part of the tables, which show the effect sizes for three types of children: those who were only exposed to the CCT, those who were only exposed to "normal" weather conditions (i.e., *no* shock) in early-life, and those who were exposed to both "positive" investments.

Our findings show little evidence that the CCT has a differential effect on weather-unaffected children. Across all outcomes, we observe that the estimates on the interaction tend to be small, are not statistically significant, and the signs of the coefficients change from positive to negative (i.e., while we find that the sign of the interaction for *not* dropping out of school is positive, that for high school completion and for the ICFES Exam is actually negative). We do find, however, that despite the null effect on the interaction, children who were exposed to adverse weather shocks in early life (e.g., were born in places with floods or droughts) and who later received the CCT-induced investments, the "main" effect of the CCT is large enough to help undo part of the decline in education caused by the floods and droughts. Hence in that sense, the CCT does seem to help reduce early-life disadvantage caused by this type of adversities. For example, Table 5 shows that children who were exposed to the weather shock experienced a decline in school retention of 5.0%, but receiving the CCT-induced investment increased the probability of being enrolled in school by 9.4%. This implies that, for a child who was both exposed to the weather shock and then received the transfer, the net positive increase would be 4.4% in school retention.

5.4 The Interaction Between Weather Conditions and CCTs by Child's Age at CCT Rollout

Motivated by the idea that investing at younger ages tends to have larger returns on human-capital, an interesting question that we now ask is: Could the effects of CCTs differ by the age at which children received the investment? If so, could this affect the potential interaction between investments and shocks? To examine heterogeneous effects by child's age, we focus on: i) outcomes that we can observe for both young and old cohorts, for instance school retention[37]; and ii), rather than focusing on the age at which a child was first enrolled in *Familias en Acción* (which is an endogenous decision from a family's perspective), we exploit the timing in the rollout, and focus on the age at which the CCT arrived at a child's municipality. The assumption here would be that the earlier the CCT arrived, the earlier he/she was able to enroll in the program.

In Table 8, we split the sample by the median child's age at CCT rollout (i.a., age 7); in particular, we compare estimates for children who were exposed to the program before and after this age. Columns 1 and 4 in Table 8 show that children who received the CCT early (i.e., age<7), experienced a much larger increase in the probability of *not* dropping out of school than those who received it later. These effects are 12% (statistically significant) vs. 4% (not statistically significant), which could suggest that timing matters and that the return of the CCT declines with the age at which the CCT was received. Columns 2 and 5 show that the effects of CCTs do not change when controlling by weather shock exposure and that the size of the coefficient on the "*no* weather shock" treatment is actually very similar across groups, confirming that the in-utero to age 3 is in fact a critical stage of human-capital development.

Finally, columns 3 and 6 present estimates on the interactions. We find that for children who receive the CCT early, the interactive effect between the CCT and the "*no* weather shock" on the probability of *not* dropping out of school, is positive and significant, suggesting that the returns of the CCT for weather-unaffected children are larger (by nearly a third with respect to the "main" effect of the CCT) than for other children who participate in the program. This result could be characterized as evidence of dynamic complementarities: that the CCT has an additional return on children who started with a higher stock of skills due to *no* exposure to the *El Niño* and *La Niña* weather shocks. For children who received the

[37] High school graduation or the ICFES exam are only observed for older cohorts.

CCT-induced investments in late childhood or adolescence, although we also find a positive (and large) effect on the interaction (i.e., 0.0035), the coefficient is not statistically significant and is almost half the size of the interaction coefficient in column 3. Considering that the "main" effect of the CCT for children who were exposed to the program at a later age is small (compared to children who received it earlier), it may help explain the smaller (and weaker) interactive effect for this group. In other words, that the later the second investment arrives the weaker the complementarity between investments.

To validate these findings, we now ask whether these differential effects by child's age at CCT rollout are observed on other outcomes. Since we cannot focus on high school graduation and ICFES test scores because these cohorts were "too old" at CCT rollout, we focus on other measures of education such as whether a child is "on time" for a given grade based on his/her age. In particular, we focus on whether a child is "on time" for 7th, 8th, or 9th grade.[38] Table 9 shows that children who were exposed to the CCT early in life experience both a larger return of the CCT and a larger and significant interactive effect of the program with the weather shock, compared to children who were exposed to the program later in life.

In the next section, we formalize these insights in the context of a theoretical model of human capital formation.

Exploring the role of Timing vs. Type of CCT-induced Investments. Now we ask whether the differential effects of *Familias en Acción* by child's age at rollout could be explained by differential timing or by the fact that children receive different types of CCT-induced investments based on their age. For instance, children 0 to 6 receive health and nutritional investments, whereas children 7 to 17 receive educational investments.[39]

To examine the role of timing and type of investments, we conduct two tests: i) One in which we try to keep child's age relatively constant around the age cutoff at which the type of investments change – i.e., focus on children between 6 and 8 years of age or between 5 and 9– and examine whether the type of investment matters and ii), one in which we try

[38] Being "on time" is constructed by comparing 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. Being "on time" for grade is an interesting outcome as it may offer additional value on a child's learning experience in the school system than, for instance, school retention.

[39] *Familias en Acción* provides cash transfers to poor families with children below age 7 with the purpose of supplementing the household's food consumption; the transfer is conditional on the child receiving all required vaccinations as well as growth development checkups, and that the mother attends courses in nutrition, hygiene, and contraception. The transfer provided to poor families with older children (ages 7–18) is intended to supplement household's spending in a child's education; the conditionality associated with the education transfer is purely based on school attendance, with a minimum of 80% of classes per academic year.

to keep the type of investment constant –i.e., focus on all children below age 7 who are eligible to receive health investments –and examine whether the timing at which they were exposed to the program matters (i.e., compare children who received the CCT from 0 to 3 vs. 4+). Results are shown in Table 10. Column 1 in panel *A* explores the role of type of investments, which suggest that, among children aged 6 to 8, those who receive the health investment first (i.e., were exposed to the program prior to age 7), experience an additional increase in school retention (by 25% of the "main" effect) than those who only receive the educational investment (i.e, were exposed to the program after age 7). However neither the "main" effect of the program nor the interaction with being age<7 at the CCT-rollout are statistically significant, perhaps due to sample size limitations. In column 2, we expand the sample by including children from 5 to 9 and we find a similar pattern as before, but now we are able to detect a positive and significant interactive effect between the CCT and receiving it prior to age 7, which is statistically significant at the 10% level. This result implies that: children who were slightly younger at the time of CCT rollout and who were therefore initially eligible to receive CCT-induced health-investments, experienced an additional 9% increase in the probability of school retention (with respect to the outcome mean), compared to children who were slightly older at CCT rollout and who were therefore only eligible to receive CCT-induced educational-investments.[40] In panel *B* column 1 we now explore the role of the timing of investments trying to keep the type of investments constant. Results suggest that among children who are eligible to receive the health investment, receiving it at ages 0 to 3 seems to have a more pronounced effect on school retention than receiving it from 4 to 7 (although these estimates are not statistically significant). When we focus on the full sample of children from 0 to 17 (and address the potential issue of small power), we find significant evidence that receiving the CCT earlier has a larger effect on children's education vs. receiving it later. In particular, children who were exposed to *Familias en Acción* at ages 0-3 experience a 19.1% increase in the probability of *not* dropping out of school, whereas those who were exposed at ages 4 to 7 experienced an 8.6% increase (not statistically significant). In sum, we conclude from these analyses that both the type of investment and the age at which children are exposed to the program matter to explain the potential effects of the CCT on tehir future outcomes. One potential concern is that children who were eligible to receive the CCT program at early ages (and exposed to initial CCT-induced health investments) are more likely to continue to participate in the program during the second phase of the program. Therefore, duration into the program could potentially confound both the type and timing effects of the CCT-induced investments shown before. To

[40]Initial CCT-induced investments refer to the type of grant that children first receive when the CCT is rolled out in their municipality.

address this concern, Table B.1 adds as an additional control eligibility to the CCT during the phase 2 according to the family's poverty score in Sisben-II. We choose to add eligibility instead of actual participation as the later is endogenous. The results of this exercise show that our conclusions regarding the type and timing of CCT-investments are robust to the inclusion of this control covariate.

Now we examine whether the the timing and type of CCT-induced investments matter for the interactive effect of the program and the weather shock. Table 11 shows results on a triple interaction between the CCT, the *no* exposure to the adverse weather shock, and the exposure to the CCT rollout prior to age 3. As we did in Table 10, we conduct analysis on two samples: children who were eligible to receive the health investments (i.e., at ages 0-6 at CCT rollout) and all children (i.e., ages 0-17 at CCT-rollout). Results shown in columns 1 and 2 display a similar pattern (although estimates are not always statistically significant): there is an extra positive effect of the program on children *not* exposed to the shock (i.e., as given by the coefficient on $CCT * No\, Shock\, Utero\, to\, Age\, 3$), however, we cannot detect an additional effect for those who received the program and were exposed to it prior to age 3, and did not experience the weather shock (the triple interaction).

In sum, the results shown here provide evidence that suggest that both timing and type of investments seem to matter for the effects of CCTs on children as well as their interactive effects with weather shocks.

6 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)[41], 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, cognitive abilities, etc.) measured at time t with $\frac{\partial f_t(.)}{\partial \theta_{it}} > 0$, also known as

[41]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.

self-productivity[42]; $I_{it} > 0$ 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., $\frac{\partial^2 f_t(.)}{\partial \theta_{it} \partial I_{it}} > 0$.

Research design and theoretical framework. 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 $\varepsilon_{i1}^{NoWeather}$); 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 for $f(.)$, we can express a child's human

[42] *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).

capital production function as[43]

$$h_i = m(\theta_{i1}, [\eta_1 (\underbrace{I_{i1}(\overset{+}{\varepsilon_{i1}^{NoWeather}})}_{\substack{\textit{No}\text{ exposure}\\ \text{to adverse}\\ \text{weather shock}}})^{\phi} + \eta_2 (\underbrace{I_{i2}(\overset{+}{\varepsilon_{i2}^{CCT}})}_{\substack{\text{CCT}\\ \text{early}\\ \text{childhood}}})^{\phi} + \eta_3 (\underbrace{I_{i3}(\overset{+}{\varepsilon_{i3}^{CCT}})}_{\substack{\text{CCT}\\ \text{late}\\ \text{childhood}}})^{\phi}]^{\frac{1}{\phi}}, x_i), \tag{10}$$

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 $j \in \{NoWeather, CCT\}$. 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. *No* weather shock exposure improve children's outcomes, $\frac{\partial h_i}{\partial \varepsilon_{i1}^{NoWeather}} > 0$;

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 complementarities between the shocks in the different periods consistent with our empirical results on the interactions. 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. $\eta_1, \eta_2 > 0$, $\frac{\partial I_{i1}}{\partial \varepsilon_{i1}^{NoWeather}}, \frac{\partial I_{i2}}{\partial \varepsilon_{i2}^{CCT}} > 0$, and

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

[43]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:

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

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

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

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 $\eta_3 \equiv \gamma_3^{I}$.

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 $\frac{\partial h_i}{\partial \varepsilon_{it}^j} > 0$ if and only if $\eta_t > 0$ and $\frac{\partial I_{it}}{\partial \varepsilon_{it}^j} > 0$, and that $\frac{\partial h_i}{\partial \varepsilon_{it}^j} \to 0$ if and only if $\eta_t \to 0$ or $\frac{\partial I_{it}}{\partial \varepsilon_{it}^j} \to 0$. $\square$

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 $\frac{\partial I_3}{\partial \varepsilon_{i3}^{CCT}} \to 0$.[44]

Second, we show the implications of these conditions for the complementarities between shocks in different periods:

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

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 $\frac{\partial^2 h_i}{\partial \varepsilon_{i1}^{NoWeather} \partial \varepsilon_{i2}^{CCT}} > 0$. From condition (2) of of lemma **1** it follows that $\frac{\partial^2 h_i}{\partial \varepsilon_{i1}^{NoWeather} \partial \varepsilon_{i3}^{CCT}} \to 0$. $\square$

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 results for the interactive effects between shocks in different periods aligned with our empirical results for the interaction, namely, dynamic complementarities when the CCT-induced investment arrives in early childhood ($\frac{\partial^2 h}{\partial \varepsilon_{i1}^{NoWeather} \partial \varepsilon_{i2}^{CCT}} > 0$), but a small interactive effect when the CCT-induced investment arrives later in a child's life ($\frac{\partial^2 h}{\partial \varepsilon_{i1}^{NoWeather} \partial \varepsilon_{i3}^{CCT}} \to 0$). In this sense, our results are consistent with leading theories on human capital formation, and shed new light on these theories, by providing evidence that the timing and type of investment matter.

7 Potential Mechanisms

In this section, we study potential mechanisms by which exposure to the weather shocks and the CCT could affect long-term educational outcomes. To conduct these analyses, we

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

rely on auxiliary data from the *Population Census* 2005[45], the *Vital Statistics Birth Records* (VSBR) 1998, 1999, and 2000[46], the *Demography and Health Study* (DHS) 1990, 1995, 2000, and 2005[47], the *Colombian Survey of Health and Nutritional Status* (ENSIN) 2010[48], and the baseline wave of the *Familias en Acción* household survey[49] (see Attanasio et al., 2004; García and Hill, 2010).

7.1 Potential Mechanisms Associated with the Weather Shocks

Research has shown that adverse environmental shocks could affect human capital through several mechanisms that include changes in maternal stress, nutrition, health, or household resources. We examine some of these channels in this section, and in particular we explore whether exposure to *El Niño* and *La Niña* affects household economic resources, food consumption/nutrition, prenatal care and breastfeeding, and children's and adolescents' health.

We begin our analyses, by examining whether the weather shock affects a family economic standing by looking at whether the shock has a contemporaneous or lagged effect on household income, poverty (SISBEN score), home ownership, or labor market participation (for the household head) using the SISBEN data. Table 12 shows that *not* being exposed to the weather shock increases household income by 6.23%, but this effect tends to dissipate after three years. No effects were found on other economic measures, suggesting that the impact of the weather shock may be transitory.

Using the baseline wave of the panel survey of *Familias en Acción*, we then examined whether the weather shock is associated with changes in food consumption (a proxy for nutrition). Table 13 suggests that families of children who were *not* exposed to the shock, were more likely to spend more money on food (an increase of 19%), and in particular to spend it on grains, fruits, and vegetables, which are be perishable food items and therefore less likely to be in supply during weather shocks.

Using the DHS data, we now explore changes in health as a potential mechanism. Results in Table 14 suggests that exposure to "normal" weather conditions during pregnancy are not associated with changes in prenatal care but do seem to increase the probability that infants are breastfeed for 6 months or longer, which is the minimum recommended length of breatsfeeding according to the World Health Organization. Columns 6 and 7 show a small

[45]The Census can be accessed here: 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.)

[46]The VSBR can be accessed here: https://www.dane.gov.co/index.php/estadisticas-por-tema/salud/nacimientos-y-defunciones/nacimientos.

[47]The DHS data can be accessed here: https://dhsprogram.com/data/.

[48]Obtained from the Colombian Family and Child Welfare Institute - *ICBF*.

[49]Obtained from the Colombian National Planning Department.

decline in both the probability of being very low birth weight (birth weight below 1,500 grams) and and being preterm (weeks of gestation below 37 weeks) (by 15%). Two plausible mechanisms that could help explain these declines in child's health at birth are maternal stress and changes in maternal nutrition during pregnancy, which are likely present in times of extreme weather events (Gluckman and Hanson, 2005).[50]

Regarding the effects on child's health and nutrition in early childhood and in later life outcomes, Table 15 shows that *no* exposure to weather shocks increases young children's height-for-age (HAZ) by 0.16 SD and is associated with a small but statistically insignificant increase on weight-for-age, a measure of child malnutrition. Previous research has found effects that are within the range of those found here. For instance, Duque (2016) found that exposure to violence in Colombia as measured by the occurrence of terrorist attacks, reduced child's HAZ by 0.09 SD. One possible explanation for the change in HAZ could be a change in household food consumption or a change in diet (e.g., protein consumption), as well as changes in the incidence of infectious disease, both of which could be plausible consequences of the weather shocks.

Using the ENSIN 2010, columns 3-5 in Table 15 shows that the effects of the weather shock are likely to persist over time. For instance, *no* weather shock exposure increases young adults' height and the probability of being overweight[51] for individuals aged 8–22 by 0.10 SD and a third of a percentage point, respectively. These findings are consistent with previous research that shows: i) adults' height is mostly explained by conditions experienced up to age 3 (Victora et al., 2010); and ii), that children in developing countries are more likely to experience the double burden of early malnutrition and a higher incidence of overweight as adults (World Health Organization, 2017).[52]

[50] 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 "normal" weather conditions in early childhood has a negative but not statistically significant effect on mortality due to these diseases. We then discriminate the cause of child mortality by the type of the 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 no exposure to droughts was associated with a decline in deaths due to respiratory causes and no floods exposure was associated with a decline in deaths due to infection causes. These results are not shown but are available upon request.

[51] 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 age 18+ and for those below age 18, the international BMI cutoff varies by age as specified by the World Health Organization.

[52] 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.

7.2 Potential Mechanisms Associated with the CCTs

Some of the mechanisms through which CCTs could help improve children's education beyond the pure conditionality may operate through reducing a family's financial burden, increasing information and social networks, or empowering mothers by making them the direct recipients of the cash transfer (Fiszbein and Schady, 2009). In this section, we explore some additional mechanisms that could help explain the positive gains observed on school retention, high school, and ICFES score, which are: school enrollment and the incidence of child labor measured right after the program was rolled-out, height, and the quality of schools that CCT recipients enroll into. To our knowledge, little research has examined the quality of schools as a potential pathway of CCTs.[53]

To examine the short term effects of CCTs on school enrollment and on child labor, we use: (i) the Census of 2005 as we cannot observe child labor in the administrative records and (ii), since we cannot observe a household's SISBEN score in the Census, we exploit the timing of *Familias en Acción* rollout across municipalities. Our strategy then compares children in municipalities that received the program earlier versus later during the program's initial expansion. Results are shown in Appendix Table A.1 and they suggest that the earlier a child was exposed to *Familias en Acción*, the larger the positive effect on school enrollment (an increase of 1.1%) and the greater the decline in child labor (a decline of 16% similar to that reported in Parker and Todd (2017)).[54] Column 3 shows that the program is also positively associated with some gains in child's height, perhaps explained by a combination of both the health investments associated with the conditionality of the program and with an income effect.

To proxy for school quality, we construct the average ICFES score for a given school in a given year when a child is first observed in the data, and we compare it to the municipality's ICFES performance in that given year.[55] In particular, we classify a school as "high-quality" by whether the school's average ICFES score exceeds the municipality's 75th percentile, and zero otherwise.[56] Results are shown in Appendix Table A.2 and they provide some evidence that suggest that the CCT does seem to affect the choice of schools that children select into. When we split the sample by whether a child is in primary vs. secondary education, we find that the effect is driven by children in secondary education, which may be consistent with

[53] Hincapié (2017) found some evidence that children in Colombia in urban and rural areas are more likely to attend schools that obtain higher end-of-high school test scores.

[54] We also examine effects by child's age. We find that there are few impacts on school enrollment (and on child labor) for younger children (ages 6 to 10) for whom enrollment rates are very high even in the absence of the program, hence the estimates that we find are mostly driven by children between 11 and 16.

[55] The R-166 from the Ministry of Education includes information on the schools where children are enrolled in each academic year that a child is observed in the data.

[56] Using other reference points provides similar results.

the fact that: i) the magnitude of the CCT transfer is larger for those children,[57] ii) there could be more heterogeneity in the quality of schools offering secondary education, and iii), children are more likely to drop out in secondary education than in primary education, hence highlighting the importance of additional incentives to keep students in the school system. In sum, this finding could suggest that, the transfer helps alleviate budget constraints that enable children to attend better schools.

8 Sources of Selection Bias and Robustness Checks

A complicating factor in the study of impacts of shocks on individual outcomes is that shocks may not only have a scarring effect on affected cohorts, but may also induce selection through mobility, fertility, or mortality (Almond, 2006; Bozzoli et al., 2009). In this section, we analyze whether the effects of *El Niño* and *La Niña* or the actual eligibility to *Familias en Acción* induce potential biases of this nature.

8.1 Mobility

We define migrants as those who were born in a different municipality to where they were interviewed in the SISBEN data. Following this definition, we find that 30% of the sample migrate over time.[58] Families living in weather-unaffected municipalities may be less likely to migrate in response to the weather conditions and if those who migrate differ from those who stay in terms of their observable and unobservable characteristics, this could bias the effects of weather shocks on children's outcomes.

To test for selective mobility across Colombian municipalities, we examine whether families whose children were *not* exposed to floods or droughts during their early years, were more or less likely to migrate and whether this probability differed by a household's observable characteristics. Appendix Table A.3 presents estimates of the effects of weather conditions on migration as well as interactions between weather conditions and a mother's education, marital status, age, and household size. Overall, we find little evidence that the probability of migrating is associated with changes in weather conditions. However, we do find some differential responses across families, for instance, those in which the parents are married, are 2.4% less likely to migrate in response to the *no* weather shock exposure. Despite these differential responses across some groups, we do not consider endogenous mobility to be a

[57]The amount of the monthly education grant varies by school grade: for families with children in primary school, the subsidy is US$ 6 (approx. 5% of the m.m.w.), whereas for those in secondary education, it is raised to US$ 12 (approx. 9% of the m.m.w.).

[58]Descriptive evidence from the population Census 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 the migrants.

major source of bias because: i) the magnitudes of the endogenous migration responses are small and ii), using information on a child's municipality of birth rather than municipality of residence is more exogeneous measure of shock exposure.

We now examine migration responses due to eligibility to the CCT. Appendix Table A.4 shows that the introduction of *Familias en Acción* does not seem to affect the probability of migration and although we find that large families are 0.6% less likely to migrate in response to the program, this effect is actually very small to drive the causal impact of the CCT on children.

8.2 Fertility

The second source of selection bias that we examine is endogenous fertility as measured by total fertility and birth spacing between siblings.[59] Results shown in Appendix Table A.5 suggest that there is little evidence of endogenous fertility induced by the weather shock, which is given by the small magnitude of the coefficients and tehir lack of statistical significance.

Appendix Table A.6 presents estimates of *Familias en Acción* on fertility. Column 1 indicates that being eligible for the program is associated with an increase in total fertility (after the focal child) of 4.4pp (with an outcome mean of 0.78 children), which seems to be driven by married mothers (who experience an increase of 4.5pp), and with little change on birth spacing decisions. Stecklov et al. (2007), using difference-in-difference models, found that CCTs can have unintended effects on fertility such as in the case of Honduras, were fertility increased by 4pp as a result of an increase in marriage rates. One possible way to account for this selective response in our models, is to control for marital status in our models (which we do).

8.3 Mortality

The estimates of early-life shocks may also be affected by selection on mortality both at birth and during early childhood: weather shocks are likely to increase the chances of dying for those with weaker health endowment. To test how *El Niño* and *La Niña* affect child mortality, we use several waves of DHS data. In particular, we examine changes in the probability that a child dies in the first month of life, before age 1, and before age 3 conditional on exposure to weather shocks in-utero, from in-utero up to age 1, and from

[59] For both outcomes, we focus on children who enter in our sample (i.e., who are within the age range of interest in this paper) and therefore exclude older older siblings who weren't unaffected by either of the shocks.

in-utero up to age 3, respectively. Appendix Table A.7 shows that there is little evidence that the weather shock is inducing changes in child mortality for both the full sample and across different groups.

We also examine how changes in weather conditions affect the cohort size and the sex ratio – two key indicators of demographic change. We use the 2005 Census data to construct these outcomes as they provide information on the total population (the SISBEN data only includes information on the poorest households). Consistent with the finding that the weather has little effect on child mortality, results in Appendix Table A.8 show that rainfall shocks in early life do not seem to be associated with changes in neither of these outcomes.

8.4 Additional Robustness Checks

Appendix B presents further evidence that our results are robust to different specifications, to using different bandwidths in our RD framework, and to accounting for potential confounding factors.

Using Alternative Definitions of Weather Shocks and CCT Exposure. We examine three alternative definitions of weather shocks: i) adding two additional windows of shock exposure such as exposure to rainfall shocks defined as changes in precipitation between the 60th and 80th percentile and between the 20th and 40th percentile precipitation (our main weather shocks are defined between the 80th and the 20th percentile); ii) distinguishing between floods vs. droughts[60] and iii), using one standard deviation shocks instead of the 80th and the 20th percentile precipitation cutoffs employed in our main specification. Table B.2 shows that adding new windows of exposure to changes in precipitation, or measuring the exposure to weather shocks based on these alternative definitions, has similar effects on children's outcomes to those shown in Table 4 (which we also report in the first panel). Of note is the small effects of floods on high school completion and on the ICFES score, which may be due to the fact that the weather shocks to which these older cohorts were exposed to in their early years were *El Niño* events that in Colombia manifests as droughts. We also examined the presence of non-linearities in weather shocks by including the squared term of the shocks in the equation. We found little evidence of non-linearities.

Regarding alternative definitions of exposure to *Familias en Acción*, we use the number of months that a child is enrolled in the program. As in the case of participation in *Familias en Acción*, duration into the program is also endogenously determined and there is not a maximum length of time that beneficiaries could be enrolled in the program, hence the decision of how long to stay depends on a household's characteristics or by the length

[60]Floods (droughts) are defined as whether a municipality's month-year rainfall is above (below) the 80th (20th) percentile of the municipality's monthly historical mean since 1980.

Familias en Acción phase I. To estimate the effects of duration into the program, we instrument treatment dosage by exploiting variation in potential exposure to the CCT taking into account the timing of the CCT rollout across municipalities, and also focusing on the age at which a child was first exposed to the program. Table B.3 reports these results, which confirm that the longer the duration, the greater the gains on children's education. Using the average duration in *Familias en Acción* 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).

Using Different Bandwidths in our RD Design. Using the bandwidth selector procedure proposed by Imbens and Kalyanaraman (2012), we found that our optimal bandwidth was 3 points below and above the poverty index cutoff for *Familias en Acción*. We now examine whether our results are robust to using alternative bandwidths around this optimal bandwidth. In particular, we use bandwidths of 2 and 4 SISBEN points around the cutoff. Appendix Table B.4 shows that using these alternative bandwidths provides qualitatively similar results to those shown in Section 5.

Potential Confounder: Exposure to Violence. One potential threat to the validity of our results could be exposure to violence shocks, as Colombia has faced for over five decades an internal armed conflict that has extended to nearly all regions of the country.[61] To examine whether violence could be a relevant omitted variable, we directly control for violence exposure in our difference-in-difference specification of the effects of weather shocks, measured as the average homicide rates from in-utero to age 3. Results are shown in Appendix Table B.5. For comparison purposes, we also present our main estimates of weather shocks (i.e., those shown in Table 4). Overall, we find that our main estimates do no seem to change when we account for children's violence exposure.

Potential Confounder: 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, and we examine the association between this indicator and *Not* being exposed to the shock and/or being eligible to receive the CCT.

[61] 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).

In Appendix Table B.6, we regress this indicator on: i) exposure to weather shocks and its interaction with socio-demographic characteristics (columns 1 and 2); ii) eligibility to the CCT and its interaction with socio-demographic characteristics (column 3 and 4); iii) both investments shocks (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 to the CCT, 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 not exposed to the weather shock are less likely to appear in the matched sample (0.3%) and children whose parents were married and were eligible to 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.

9 Conclusions

This paper provides new evidence on the interaction between early-life endowments and subsequent health and educational investments by focusing on two policy-relevant shocks that affect the lives of millions of household across the world: adverse weather events and conditional cash transfer programs. We combine a difference-in-difference framework of exposure to weather shocks with a RD design of CCT-induced investments to examine whether 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 differential return of the CCT-induced investments than other children enrolled in the program but who were exposed to the adverse weather shock.

We show that both the timing and type of CCT-induced investments matter for both the "main" effects of CCTs as well as their interactive effects with weather shocks. When the CCT-induced investments occur in sensitive periods of human capital formation (e.g., early childhood), the returns are large and their interactive effects with weather conditions suggest that the returns of the program are even larger for weather-unaffected children. In contrast, CCT-induced investments that come relatively late in childhood (e.g., adolescence) have a smaller "main" effect and a smaller or zero interactive effect with the weather shock. Regarding type, we show that initial CCT-induced health investments tend to have larger returns on children's outcomes than initial CCT-induced educational investments. These findings shed new light on the developmental production function of human capital, as they provide novel evidence on how dynamic complementarities relate to sensitive periods of child development. In that sense, our results help explain, to some extent, why the emerging literature on interactions has found mixed results.

Although our results show that children affected by whether shocks tend to experience a lower return of the CCT compared to un-affected children, we do find that the overall effect of the program helps undo the damage caused by early-life shocks. 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 with increasing unpredictability in 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 more likely to be affected by weather shocks than other countries, in part because their economic activity is more dependent on agriculture and in part because they have lower infrastructure, less-adequate health systems, weaker credit markets, and lower safety nets (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 dissipate heat or protect themselves under extreme weather conditions (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.

Last, although we find that CCTs do not fully eliminate gaps caused by adverse weather shocks, the results of this paper highlight the importance of intervening early in children's lives to maximize program effectiveness and minimize initial gaps across groups.

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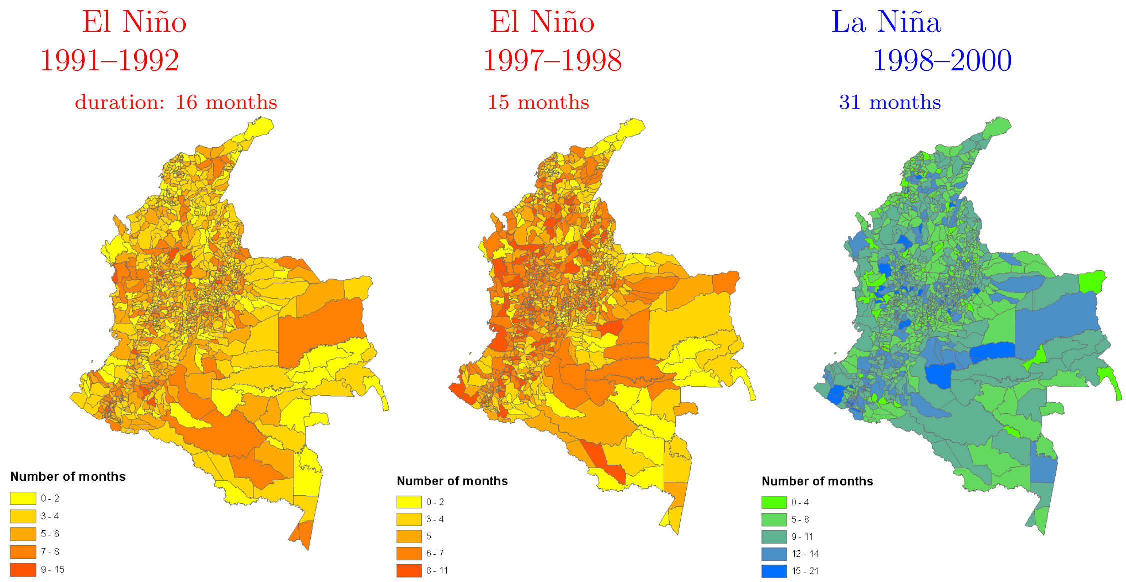
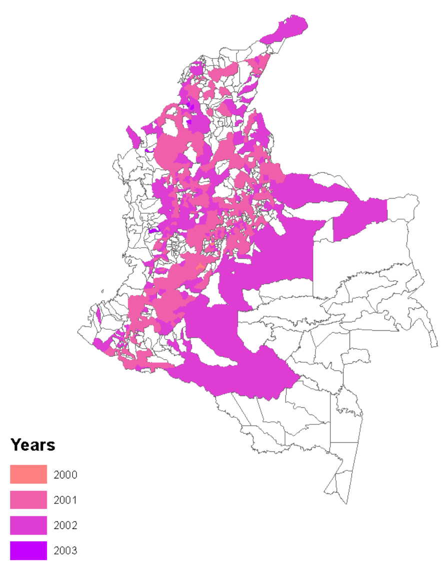
10 Figures and Tables

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



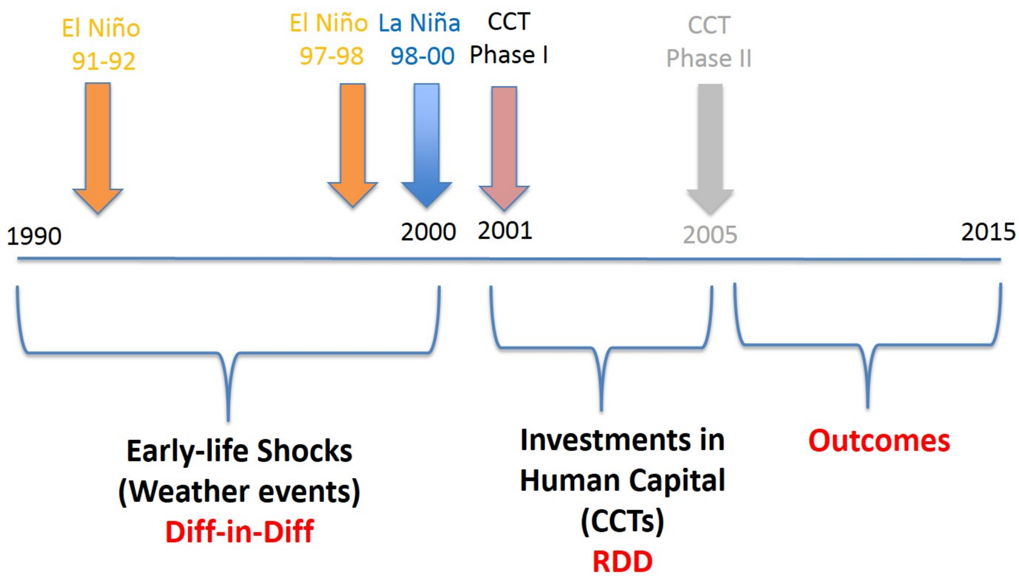
Note: The maps show the geographic variation in exposure to weather shocks during the climate events of interest. Each specific region corresponds to a municipality. The map displays the intensity of each shock measured as the number of months of extreme weather (i.e., a municipality's month–year precipitation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

Figure 2: Rollout of *Familias en Acción*—Phase I



Source: Ministry of Social Protection, Colombia.

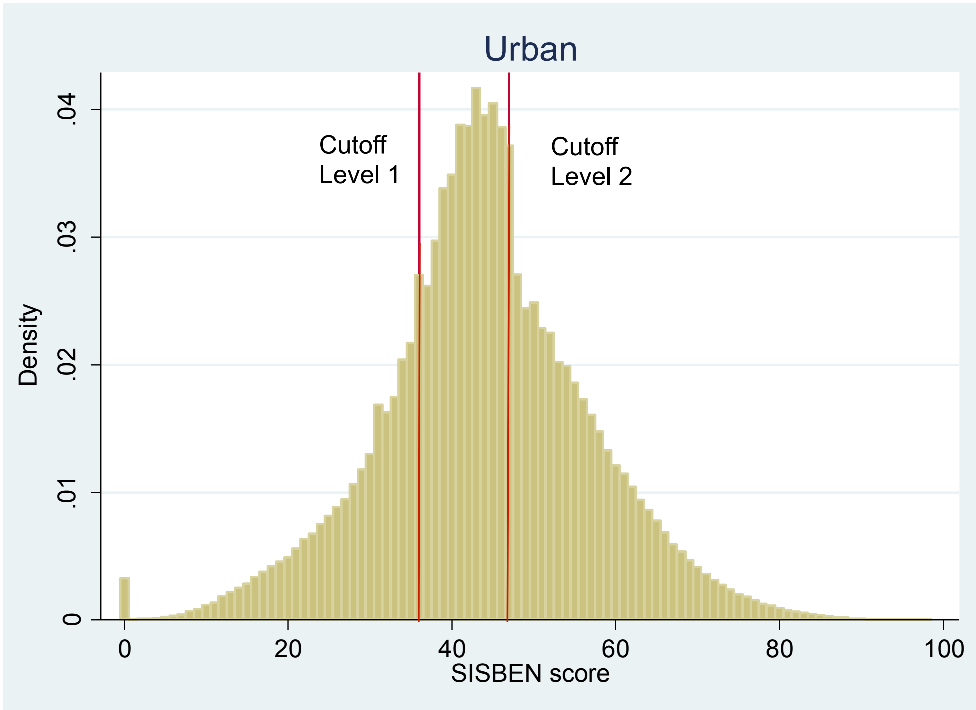
Figure 3: Research Design



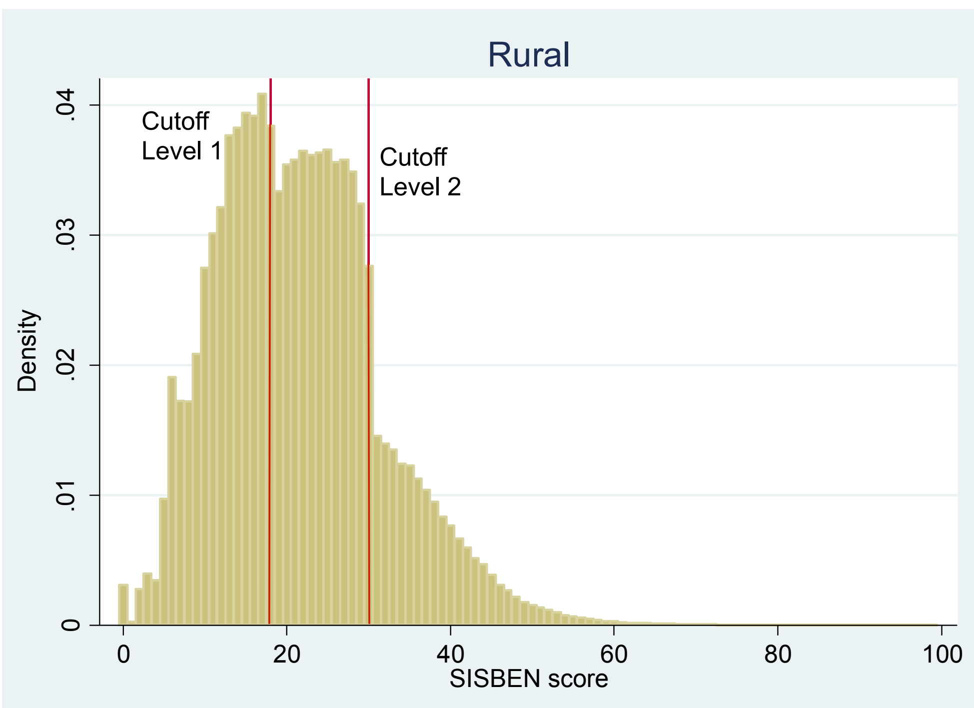
Note: The figure shows the chronological timing of the weather shocks during the 1990s and the introduction and later expansion of *Familias en Acción* in the 2000s (in this paper we only focus on the intial phase of *Familias en Acción*). The outcomes of interest are measured from 2005 and up to 2015.

Figure 4: Distribution of the SISBEN Score in Urban and Rural Areas

Panel A: Urban

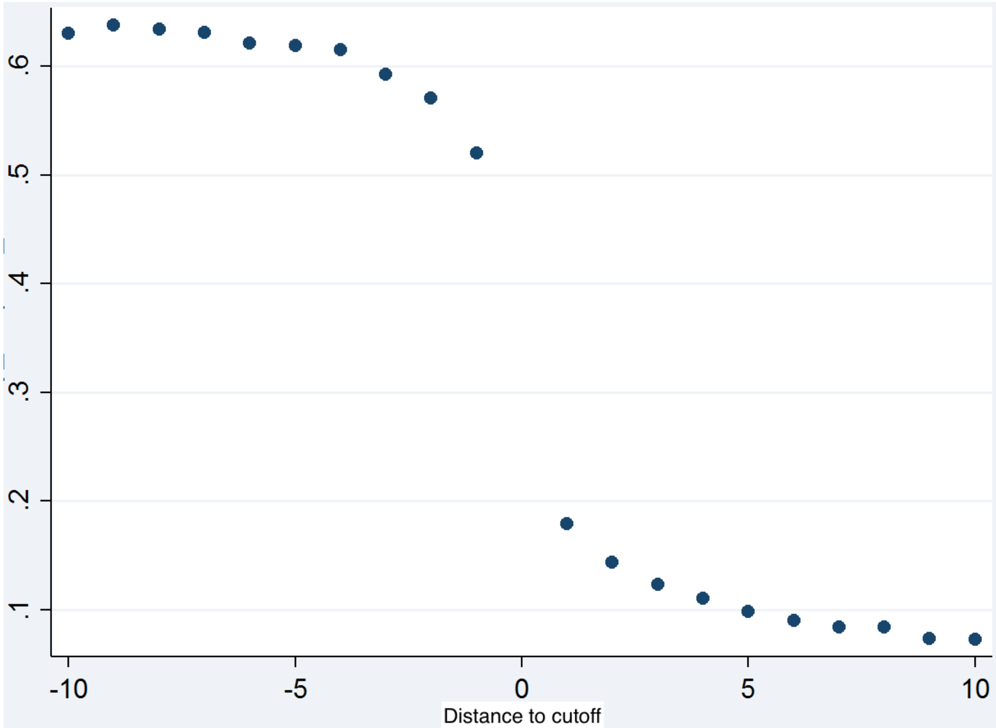


Panel B: Rural



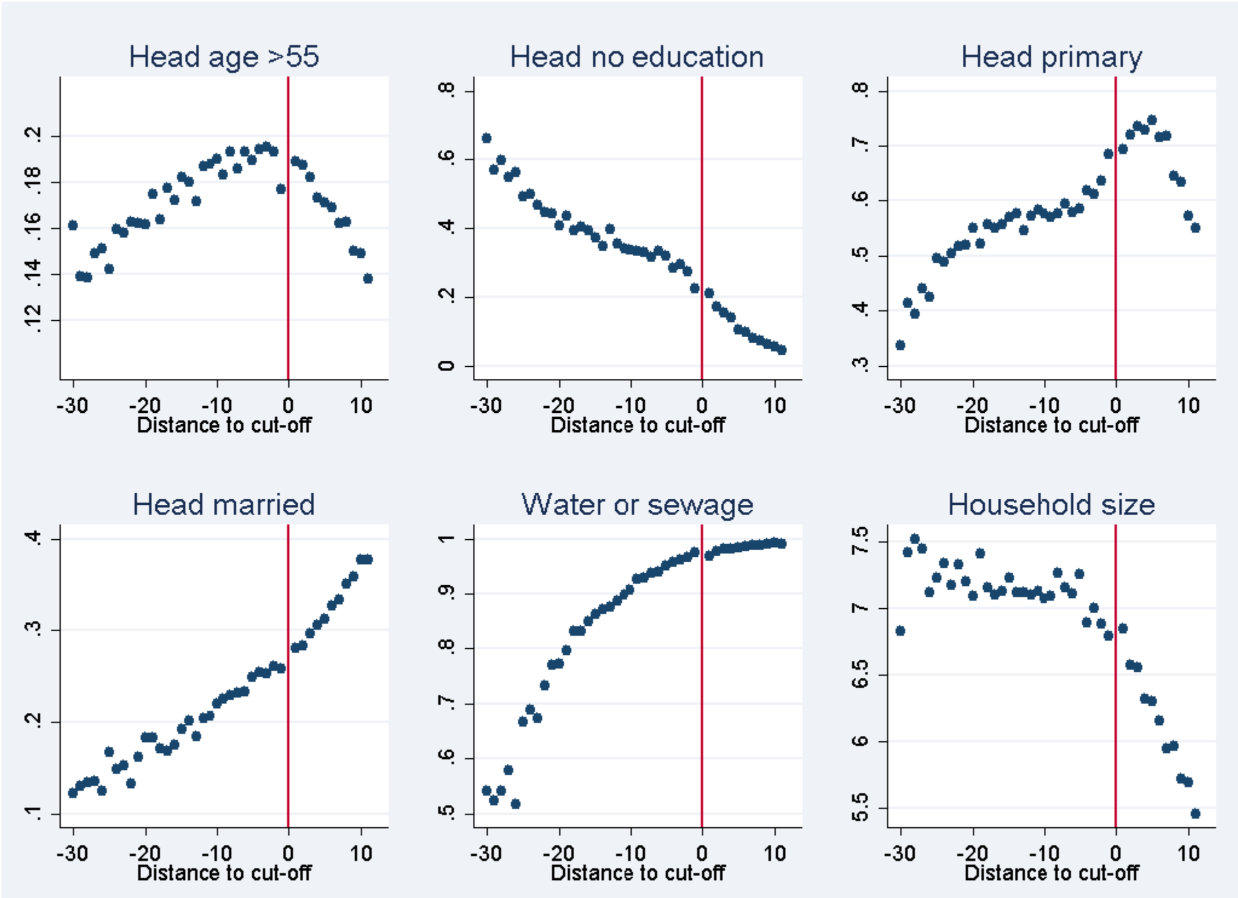
Note: Sample includes families across the whole SISBEN score distribution (Levels 1 through 6) in the "SISBEN I" (or Census of the poor) database. The cutoff between Levels 1 and 2 determines eligibility to *Familias en Acción* whereas the cutoff between Levels 2 and 3 determines eligibility to all other major social programs such as subsidized healthcare or retirement pensions.

Figure 5: Participation in *Familias en Acción*, Phase I



Note: Sample includes families 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 *Familias en Acción* cutoff of 36 in urban areas).

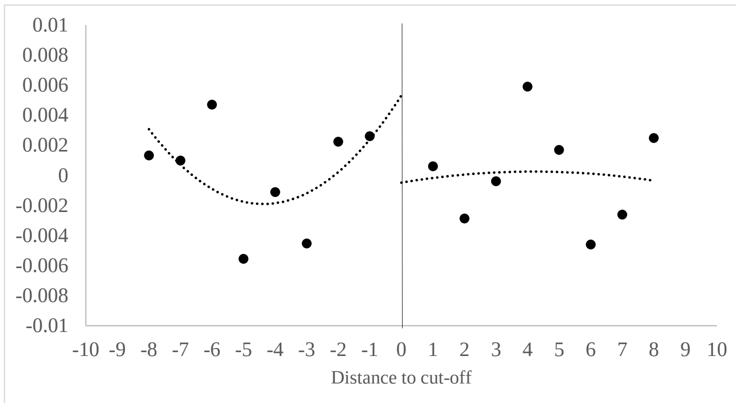
Figure 6: Sociodemographic Characteristics Around the Cutoff for *Familias en Acción*



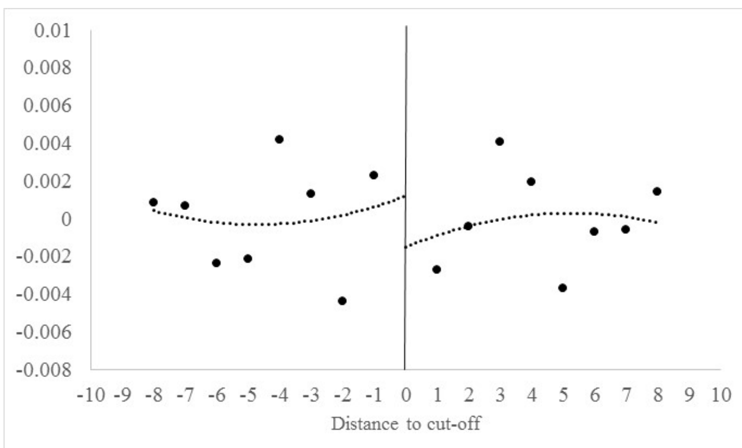
Note: Sample includes families in SISBEN Levels 1 and 2 around the cutoff of *Familias en Acción* eligibility (SISBEN Level 3 begins at 12 points above the cutoff and is not shown in the figures). Each dot in the figures represents the average value of each household characteristic at each bin of one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

Figure 7: Educational Outcomes Around the SISBEN Cutoff for *Familias en Acción*

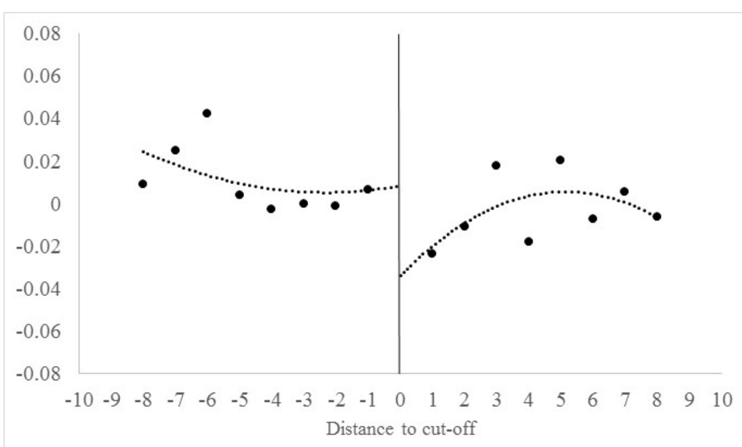
Panel A: *Not* School Dropout



Panel B: High School Completion



Panel C: End of High School ICFES Exam



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

Table 1: Eligibility for *Familias en Acción* based on the SISBEN Score 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

Source: National Planning Department.

Table 2: Association between Weather Shocks 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)
No 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)
No 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: Sample includes children in the urban segment of the municipalities targeted by the CCT Phase 1. Models include municipality, month, and year of birth FE; errors are clustered at the municipality level. The "No Shock" variable refers to *no* exposure to the flood/drought shock in a child's developmental period, in-utero up to age 3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3: Association Between Exposure to Weather Shocks and CCTs

	Eligible for CCT	Distance to cutoff eligibility	CCT Take-up
	(1)	(2)	(3)
No 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: Sample includes children in the urban segment of the municipalities targeted by the CCT Phase 1. Models include municipality, month, and year of birth FE; errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: The Effects of Weather Shocks on Children's Education

	No School Dropout		High School Completion		ICFES Exam (SD)	
	(1)	(2)	(3)	(4)	(5)	(6)
No Shock Utero to Age 3	0.0038***	0.0035***	0.0042***	0.0041***	0.0055***	0.0057**
	[0.0007]	[0.0011]	[0.0011]	[0.0017]	[0.0016]	[0.0033]
N	259,347	68,884	131,509	33,410	102,987	26,386
Sample	Full	RD	Full	RD	Full	RD
Mean	0.57	0.57	0.46	0.46	0	0
Effect size	5.3%	5.0%	7.3%	7.1%	0.04 SD	0.05 SD

Note: Sample includes children in the urban segment of the municipalities that participated in the rollout of *Familias en Acción*, Phase I. 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 the optimal bandwidth sample and includes all children of families with SISBEN score three points below and 3 points above the cutoff. Models include 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, household head education, age, family size, marital status, access to water/sewage, and year of SISBEN interview dummies. The "No Shock" variable is measured as the number of months that a child was not 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 mean since 1980) 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 5: The Interaction between Weather Shocks and CCTs on *Not* Dropping-out of School

	No School Dropout		
	(1)	(2)	(3)
CCT	0.0538*	0.0536*	0.0681**
	[0.0289]	[0.0288]	[0.0322]
No Shock Utero to Age 3		0.0035***	0.0029**
		[0.0011]	[0.0011]
CCT * *No* 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=Y, *No* Shock=N)	9.5%	9.4%	11.9%
Effect (CCT=N, *No* Shock=Y)		4.9%	4.1%
Effect (CCT=Y, *No* Shock=Y)	9.5%	14.3%	18.5%

Note: Sample includes children in the urban segment of the municipalities that participated in the rollout of *Familias en Acción*, Phase I. Models include 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, household head education, age, family size, marital status, access to water/sewage, and year of SISBEN interview dummies. The "No Shock" variable is measured as the number of months that a child was not 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 mean since 1980) during the events of interest (i.e., El Niño and La Niña shocks of the 1990s) from in utero to age 3. The CCT refers to whether a child received the CCT investment; this variable is instrumented using the eligibility to the program based on the SISBEN score. The interaction effect is instrumented using the *no* weather shock interacted with eligibility as the instrument (see section 4 for details). The bottom of the table shows the implied effect size for three types of children: (i) children who were *not* exposed to the weather shock (which on average lasted 8-months during a child's early stages); (ii) children who were only exposed to the CCT; and (iii), children who were exposed to both the *no* weather shock and the CCT. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6: The Interaction between Weather Shocks and CCTs on High School Completion

	High School Completion		
CCT	0.1326*	0.1354*	0.1213*
	[0.0750]	[0.0719]	[0.0699]
No Shock Utero to Age 3		0.0046**	0.0055**
		[0.0018]	[0.0022]
CCT * *No* Shock Utero to Age 3			-0.0007
			[0.0037]
N	33,410	33,410	33,410
Mean	0.42	0.42	0.42
Effect (CCT=Y, *No* Shock=N)	30.4%	31.0%	28.6%
Effect (CCT=N, *No* Shock=Y)		8.8%	10.5%
Effect (CCT=Y, *No* Shock=Y)		39.8%	37.7%

Note: Sample includes children in the urban segment of the municipalities that participated in the rollout of *Familias en Acción*, Phase I. Models include 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, household head education, age, family size, marital status, access to water/sewage, and year of SISBEN interview dummies. The "No Shock" variable is measured as the number of months that a child was not 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 mean since 1980) during the events of interest (i.e., El Niño and La Niña shocks of the 1990s) from in utero to age 3. The CCT refers to whether a child received the CCT investment; this variable is instrumented using the eligibility to the program based on the SISBEN score. The interaction effect is instrumented using the *no* weather shock interacted with eligibility as the instrument (see section 4 for details). The bottom of the table shows the implied effect size for three types of children: (i) children who were *not* exposed to the weather shock (which on average lasted 8-months during a child's early stages); (ii) children who were only exposed to the CCT; and (iii), children who were exposed to both the *no* weather shock and the CCT. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 7: The Interaction between 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]
No Shock Utero to Age 3		0.0053	0.0055
		[0.0033]	[0.0041]
CCT * *No* Shock Utero to Age 3			-0.0008
			[0.0083]
N	27,275	27,275	27,275
Mean	0	0	0
Effect (CCT=Y, *No* Shock=N)	0.13SD	0.13SD	0.13SD
Effect (CCT=N, *No* Shock=Y)		0.04SD	0.04SD
Effect (CCT=Y, *No* Shock=Y)	0.13SD	0.17SD	0.16SD

Note: Sample includes children in the urban segment of the municipalities that participated in the rollout of *Familias en Acción*, Phase I. Models include 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, household head education, age, family size, marital status, access to water/sewage, and year of SISBEN interview dummies. The "No Shock" variable is measured as the number of months that a child was not 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 mean since 1980) during the events of interest (i.e., El Niño and La Niña shocks of the 1990s) from in utero to age 3. The CCT refers to whether a child received the CCT investment; this variable is instrumented using the eligibility to the program based on the SISBEN score. The interaction effect is instrumented using the *no* weather shock interacted with eligibility as the instrument (see section 4 for details). The bottom of the table shows the implied effect size for three types of children: (i) children who were *not* exposed to the weather shock (which on average lasted 8-months during a child's early stages); (ii) children who were only exposed to the CCT; and (iii), children who were exposed to both the *no* weather shock and the CCT. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8: The Interaction between Weather Shocks and CCTs on *Not* Dropping-out of School by Child's Age at CCT Rollout

	No School Dropout					
	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]
No Shock Utero to Age 3		0.0065***	0.0046***		0.0048***	0.0036*
		[0.0014]	[0.0017]		[0.0015]	[0.0022]
CCT * *No* Shock Utero to Age 3			0.0062**			0.0035
			[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=Y, *No* Shock=N)	11.7%	11.7%	24.4%	3.7%	3.6%	5.9%
Effect (CCT=N, *No* Shock=Y)		9.0%	6.3%		6.9%	5.1%
Effect (CCT=Y, *No* Shock=Y)	11.7%	20.7%	39.3%	3.7%	10.5%	16.0%

Note: Sample includes children in the urban segment of the municipalities targeted by *Familias en Acción*, Phase I. Models include municipality, month, and year of birth FE; 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/sewage, 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 eligible to receive the education grant. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 9: The Interaction between 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	
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]
No 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 * *No* 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
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]
No 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 * *No* 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: Sample includes children in the urban segment of the municipalities targeted by *Familias en Acción*, Phase I. Models include municipality, month, and year of birth FE; 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/sewage, 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 eligible to receive the education grant. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 10: The Effects of CCTs on Children's Education: Timing vs. Type of Investment

	No School Drop-out	
	(1)	(2)
Panel A: Exploring the role of type (holding constant age)		
CCT	0.0890	0.0742*
	[0.0633]	[0.0442]
CCT * Rollout <age 7	0.0222	0.0532*
	[0.0411]	[0.0317]
N	15,288	30,205
Sample eligible for	health or education	health or education
Age at CCT rollout	6-8	5-9
Panel B: Exploring the role of timing		
CCT	0.0624	0.0283
	[0.0396]	[0.0270]
CCT * Rollout <age 3	0.0291	0.0807**
	[0.0391]	[0.0352]
CCT * Rollout at ages 4-7		0.0207
		[0.0194]
N	36,380	68,884
Sample eligible for	health	health or education
Age at CCT rollout	0-7	0-17

Note: Sample includes children in the urban segment of the municipalities targeted by *Familias en Acción*, Phase I. Models include municipality, month, and year of birth FE; 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/sewage, and year of SISBEN interview dummies. "CCT - rolled-out<age 3" refers to children who were age 3 or less when the CCT was rolled-out in their municipality, and "CCT - rolled-out< at ages 4-7" and "CCT - rolled-out<age 7" are defined similarly. Children <age 7 are eligible to receive the health grant. Children >=age 7 are eligible to receive the education grant. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 11: The Interaction between Weather Shocks and CCTs: Timing vs. Type of Investment

	No School Drop-out	
	(1)	(2)
CCT	0.1088*	0.0670**
	[0.0601]	[0.0319]
No Weather Shock Utero to Age 3	0.0046***	0.0028**
	[0.0017]	[0.0012]
CCT * *No* Shock Utero to Age 3	0.0048	0.0019
	[0.0033]	[0.0018]
CCT * Roll-out<age 3	0.0338	0.0709
	[0.1109]	[0.1001]
CCT * Roll-out<age 3 * *No* Shock Utero to Age 3	0.0005	0.0027
	[0.0089]	[0.0085]
N	36,380	68,884
Sample eligible for	health	health or education
Age at CCT rollout	0-7	0-17

Note: Sample includes children in the urban segment of the municipalities targeted by *Familias en Acción*, Phase I. Models include municipality, month, and year of birth FE; 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/sewage, and year of SISBEN interview dummies. "CCT - rolled-out<age 3" refers children who were age 3 or less when the CCT was rolled-out in their municipality. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 12: The Effects of Weather Shocks on Household Economic Resources

	ln(HH income)	Sisben score	Home ownership	Head works
	(1)	(2)	(3)	(4)
No Weather Shock in t	0.0114*	0.0018	-0.0001	0.0007
	[0.0067]	[0.0069]	[0.0031]	[0.0017]
No Weather Shock in t-1	0.0146	-0.0014	0.0012	0.0036
	[0.0101]	[0.0081]	[0.0047]	[0.0041]
No Weather Shock in t-2	0.0184	-0.0084	-0.0072	0.0015
	[0.0118]	[0.0101]	[0.0070]	[0.0052]
No Weather Shock in t-3	0.0184	0.0045	-0.0156	-0.0028
	[0.0167]	[0.0171]	[0.0136]	[0.0054]
No 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: Sample includes families of the sample children in the SISBEN data and in our main specifications. Models include controls for child's gender, household head education level, marital status, family size, access to water or sewage, and year, month, municipality of Sisben interview. "Head works" is defined for the active population (those working and looking for a job). The "No Shock" variable refers to *no* exposure to the flood/drought shock in-utero . Standard errors are clustered at the municipality level. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 13: The Effects of Weather Shocks on Household Food Consumption Using the *Familias en Acción* Baseline Survey

	ln($ spent on...				
	animal protein)	carbs)	grains)	fruits, veggies)	total food)
	(1)	(2)	(3)	(4)	(5)
No 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: Sample includes all children in the baseline wave of the *Familias en Acción* household survey collected in 2000. The sample is restricted to families living in the urban areas. Models include individual covariates such as 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. The "No Shock" variable refers to *no* exposure to the flood/drought shock in-utero. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 14: The Effects of Weather Shocks on Prenatal Care and Breastfeeding

	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)
No Weather Shock Utero	-0.0010	0.0116	-0.0001	0.0160**	-0.0006	-0.0002***	-0.0015**
	[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	0.002	0.08
Dataset	DHS	DHS	DHS	DHS	VSBR	VSBR	VSBR

Note: 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 areas. Models include individual covariates such as 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. Robust standard errors in brackets. The models using VSBR also include controls for health insurance and for birth order. The "No Shock" variable refers to *no* exposure to the flood/drought shock in-utero . Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 15: The Effects of Weather Shocks on Children's Health in the Medium-term (MT) and Long-term (LT) Using the DHS and ENSIN

	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)
No 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: Sample includes all children $<$ 60 months of age in DHS 1995, 2000, and 2005, while de models using the ENSIN include children born between 1988 and 2000. The sample is restricted to families living in the urban areas. Models include individual covariates such as 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. The "No Shock" variable refers to *no* exposure to the flood/drought shock in a child's developmental period, in-utero up to age 3. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A Appendix:

A.1 Additional Potential Mechanisms

Table A.1: The Effects of CCTs on School Enrollment, Child Labor, and Height in the Census and ENSIN Datasets

	Attends school	Child Labor	Height (Z-score)
	(1)	(2)	(3)
CCT exposure (using the rollout of *Familias en Acción*)	0.0100***	-0.0049**	0.0971*
	[0.0035]	[0.0024]	[0.0508]
Dataset	Census 2005	Census 2005	ENSIN 2010
N	137,501	108,459	2,821
Mean	0.94	0.03	-0.06
Effect size	1.1%	-16.3%	0.10 SD

Note: The sample includes children in the Census 2005 and in the ENSIN 2010 born between 1988 and 2000 and observed in the urban segment of the municipalities that participated in the rollout of *Familias en Acción*, Phase I. CCT exposure is defined as the duration to which a child is exposed to the program in his/her municipality of residence since the program's arrival. The models include individual covariates (child's gender, race, age) and mother controls (age, race, education, marital status) as dummy variables. Child's year and month of birth FE, and municipality of residence FE are included. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.2: The Effects of CCTs on the Probability that a Child Attends a "High Quality" Public School in the Administrative data

	Child Attends a "High Quality" Public School		
	Full sample	Primary school	Secondary school
	(1)	(2)	(3)
CCT (using the RD design)	0.0367*	-0.0168	0.0936**
	[0.0223]	[0.0487]	[0.0389]
N	64,065	64,065	64,065
Mean	0.426	0.423	0.432
Effect size	8.6%		21.6%

Note: See Table 5 for more information on the sample and controls. The outcome is defined as whether the school that a child attends, has an average ICFES score that is above the municipality's 75th percentile in the year in which a child was first observed in the data (i.e., the core dataset of the Ministry of Education, the R-166, described in Section 3).Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.2 Selection Concerns: Mobility

Table A.3: The Effects of Weather Shocks on Mobility

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

Note: See Table 5 for more information on the sample and controls. Migrants are defined as those who were born in a different municipality to 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 A.4: 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 5 for more information on the sample and controls. Migrants are defined as those who were born in a different municipality to where they were sampled in the SISBEN data. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.3 Fertility

Table A.5: The Effects of Weather Shocks on Fertility Outcomes

	Total fertility after "focal" child		Birth spacing after "focal" child	
	(1)	(2)	(3)	(4)
No Shock Utero to Age 3	0.0038	-0.0077	-0.1168	0.0808
	[0.0032]	[0.0297]	[0.0625]	[0.2530]
No Shock * Mom has no educ		-0.0102		-0.1965
		[0.0062]		[0.0885]
No Shock * Mom has primary educ		-0.0074		-0.1093
		[0.0056]		[0.0704]
No Shock * Mom is married		-0.0025		0.0709
		[0.0021]		[0.0435]
No Shock * Mom's age		0.0006		-0.0022
		[0.0014]		[0.0116]
No 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 5 for more information on the sample and controls. Total fertility after "focal" child refers to the number of younger siblings born after a child in our sample of interest. Birth spacing after "focal" child refers to the number of months between a child in our sample and the next younger sibling (following birth order). Standard errors are clustered at the state level. $^{***}p< 0.01$, $^{**}\ p< 0.05$, $^{*}p< 0.1$.

Table A.6: 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 5 for more information on the sample and controls. Total fertility after "focal" child refers to the number of younger siblings born after a child in our sample of interest. Birth spacing after "focal" child refers to the number of months between a child in our sample and the next younger sibling (following birth order). Standard errors are clustered at the state level. $***p < 0.01$, $**\ p < 0.05$, $*p < 0.1$.

A.4 Mortality

Table A.7: The Effects of Weather Shocks 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)
No Shock1	-0.0012	-0.0187	0.0002	0.0108	-0.0003	-0.0041
	[0.0011]	[0.0125]	[0.0011]	[0.0149]	[0.0011]	[0.0212]
No Shock * Mom has primary educ		0.0041		-0.0086		-0.0048
		[0.0046]		[0.0062]		[0.0039]
No Shock * Mom has HS or <		0.0040		-0.0068		-0.0051
		[0.0047]		[0.0062]		[0.0040]
No Shock * Mom has >HS		0.0056		-0.0076		-0.0058
		[0.0048]		[0.0063]		[0.0041]
No Shock * Mom is married		0.0030		0.0013		0.0013
		[0.0022]		[0.0015]		[0.0022]
No Shock * Mom's age		0.0010		-0.0003		0.0008
		[0.0009]		[0.0010]		[0.0013]
No Shock * Mom's age squared		0.0000		0.0000		0.0000
		[0.0000]		[0.0000]		[0.0000]
No 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
R^2	0.033	0.034	0.042	0.043	0.430	0.442

Note: Sample includes children <age 5 in the Demography and Health Survey (DHS), waves 1990, 1995, and 2000 and in urban areas. Models include controls for child's gender, age, and 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 current municipality for a longer period than a child's age. The "No Shock" in columns 1 and 2 only captures the in-utero period, whereas that in columns 3 and 4 captures the period from in-utero up to age 1, and that in columns 5 and 6, from in-utero up to age 3. The sample in columns 3 and 4 is restricted to ages 1+, whereas that in columns 5 and 6, includes 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 A.8: The Effects of Weather Shocks on Selective Survival in the Census

	Cohort size		Sex ratio	
	Urban areas	Urban areas and CCT municipalities	Urban areas	Urban areas and CCT municipalities
	(1)	(2)	(3)	(4)
No 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: Sample includes information from the population Census 2005 at the municipality-year-month levels and is restricted to urban areas only. Models include municipality, month, and year of birth FE. The "No Shock" variable refers to *no* exposure to the flood/drought shock in a child's developmental period, in-utero up 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 female born in a given municipality, year, and month. The data was downloaded from IPUMS International. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B Appendix: Robustness checks

Table B.1: The Effects of CCTs on Children's Education: Timing vs. Type of Investment - control for eligibility to CCT phase 2

	No School Drop-out	
	(1)	(2)
Panel A: Exploring the role of type (holding constant age)		
CCT	0.0742*	0.0552
	[0.0442]	[0.04378]
CCT * Roll-out <age 7	0.0532*	0.0521*
	[0.0317]	[0.0287]
N	30,205	
Sample eligible for	Health or education	
Age at CCT rollout	5-9	
Control for eligible to CCT Phase 2		X
Panel B: Exploring the role of timing		
CCT	0.0283	0.0113
	[0.0270]	[0.0271]
CCT * Roll-out <age 3	0.0807**	0.0870**
	[0.0352]	[0.0351]
CCT * Roll-out at ages 4-7	0.0207	0.0244
	[0.0194]	[0.0193]
N	68,884	
Sample eligible for	Health or education	
Age at CCT rollout	0-17	
Control for eligible to CCT Phase 2		X

Note: Sample includes children in the urban segment of the municipalities targeted by *Familias en Acción*, Phase I. Models include municipality, month, and year of birth FE; 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/sewage, and year of SISBEN interview dummies. "CCT - rolled-out<age 3" refers to children who were age 3 or less when the CCT was rolled-out in their municipality, and "CCT - rolled-out< at ages 4-7" and "CCT - rolled-out<age 7" are defined similarly. Children <age 7 are eligible to receive the health grant. Children >=age 7 are eligible to receive the education grant. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.2: The Effects of Weather Shocks on Children's Education Using Alternative Definitions of Weather Shock Exposure

	No School Dropout	High School Completion	ICFES score (SD)
	(1)	(2)	(3)
Main specification			
No Shock Utero to Age 3	0.0051***	0.0051***	0.0081**
(percentile 80-100 & 0-20)	[0.0011]	[0.0019]	[0.0034]
Effect size	6.5%	8.9%	0.082 SD
Main specification + additional thresholds of exposure			
No Shock Utero to Age 3	0.0050***	0.0030*	0.0590**
(percentile 80-100 & 0-20)	[0.0008]	[0.0019]	[0.0030]
No Shock Utero to Age 3	-0.0014	0.0019	0.0018
(percentile 60-80 & 40-20)	[0.0010]	[0.0019]	[0.0031]
Effect size	10.5%	5.2%	0.05 SD
Separating between Droughts and Floods			
No Droughts Utero to Age 3	0.0039**	0.0063***	0.0254***
(percentile 0-20)	[0.0009]	[0.0020]	[0.0093]
No Floods Utero to Age 3	0.0029***	0.0005	0.0074*
(percentile 80-100)	[0.0010]	[0.0047]	[0.0041]
Effect size	6.3%	11.8%	0.081 SD
1 SD Shocks			
No 1 SD Shock Utero to Age 3	0.0030***	0.0068***	0.0101***
	[0.0011]	[0.0012]	[0.0043]
Effect size	6.1%	7.5%	0.084 SD
N	68,884	33,754	26,386
Mean	0.43	0.46	0 SD

Note: See Table 4 for more information on the sample and controls. The weather shock is measured using alternative definitions. Panel 1 (main specification): shocks are measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above the 80th or below the 20th percentile of the monthly-municipality historical precipitation mean since 1980) during the events of interest (i.e., El Niño and La Niña shocks of the 1990s) in the relevant developmental stages. Panel 2 (additional thresholds of exposure): adds to the main specification the number of months of exposure to weather shocks between the 60th and 80th percentile and 40th to 20th percentile. Panel 3 (separating between floods and droughts): Floods are measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above the 80th percentile of the monthly-municipality historical mean since 1980) in the relevant developmental stages, whereas droughts are measured using the 20th percentile or below. Panel 4 (using 1 SD shocks): shocks are measured as the number of months of extreme weather (i.e., a municipality's month-year rainfall above 1SD or below 1SD of the monthly-municipality historical mean since 1980) during the events of interest (i.e., El 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 B.3: The Effects of CCTs (measured in months) on Children's Education

	No School Dropout	High School Completion	ICFES score (SD)
	(1)	(2)	(3)
Main specification			
CCT Take-up	0.0538*	0.1431**	0.1904**
	[0.0289]	[0.0723]	[0.0804]
Effect size	12.5%	30.4%	0.19 SD
Using months in the program			
CCT Duration	0.0014**	0.0025	0.0033*
	[0.0006]	[0.0019]	[0.0017]
Effect size	15.6%	26.1%	0.16 SD
N	68,884	33,754	26,386
Mean	0.43	0.46	0

Note: See Table 5 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 the potential exposure to the CCT, calculated using the CCT rollout date and child's age at rollout. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.4: The Interaction Between CCT Eligibility and Weather Shocks Using Alternative RD Design Bandwidths

	No School Dropout				High School Completion				ICFES Score (SD)			
Points around the cutoff	2 points		4 points		2		4		2		4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CCT	0.0400	0.0605	0.0555**	0.0630**	0.0872*	0.0790	0.0501	0.0482	0.1454	0.1015	0.0802	0.0767*
	[0.0367]	[0.0412]	[0.0241]	[0.0265]	[0.0607]	[0.0587]	[0.0532]	[0.0324]	[0.1004]	[0.1095]	[0.0428]	[0.0425]
No Shock Utero		0.0022*		0.0022**		0.0038**		0.0025**		0.0049		0.0057
to Age 3		[0.0013]		[0.0010]		[0.0016]		[0.0012]		[0.0061]		[0.0040]
CCT * *No* Shock		0.0026		0.0009		-0.0016		-0.0004		-0.0007		-0.0016
Utero to Age 3		[0.0024]		[0.0015]		[0.0044]		[0.0031]		[0.0128]		[0.0079]
N	45,074	45,074	90,826	90,826	22,152	22,152	44,816	44,816	17,142	17,142	35,158	35,158

Note: See Table 5 for more information on the sample and controls. The optimal bandwidth is 3 points at each side of the SISBEN cutoff. The first two columns for each outcome use a 2 point bandwidth around the cutoff whereas the last two columns for each outcome use a 4 point bandwidth around the cutoff. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.5: The Effects of Weather Shocks on Children's Education Controlling for Violence Shocks

	No School Dropout		High School Completion		ICFES Exam score (SD)	
	(1)	(2)	(3)	(4)	(5)	(6)
No Shock Utero to Age 3	0.0035***	0.0036***	0.0051***	0.0051***	0.0081**	0.0079**
	[0.0011]	[0.0011]	[0.0019]	[0.0019]	[0.0034]	[0.0037]
N	68,884	68,884	33,754	33,754	26,386	26,386
Violence controls		X		X		X

Note: See Table 4 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 and up 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 B.6: Selective Matching, Weather Shocks and CCT Eligibility

	Weather shock		CCT eligibility		Both shocks	Add interaction
	(1)	(2)	(3)	(4)	(5)	(6)
No 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 * No 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 *Familias en Acción*, Phase 1. The dependent variable is a dummy equals to 1 if a child appears in the Ministry of Education data (R-166 or ICFES). 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/sewage, and year of SISBEN interview dummies. Each column comes from a separate regression. Standard errors are clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

C Appendix: Additional Tables

Table C.1: 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 early-life shock (dummy)	0.88	0.88
Duration of early-life shocks (months)	7.97	8.12
	[5.78]	[5.83]
Not a school dropout	0.57	0.57
High school completion	0.46	0.43
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 *Familias en Acción* used in the RD framework. The period of early life is defined as the period from in-utero up to age 3.

Table C.2: First Stage: The Effects of CCT Eligibility on CCT Take-up Across Three Samples

	CCT Take-up		
Sample for:	*No* School Dropout	High School Completion	ICFES Exam (SD)
	(1)	(2)	(3)
CCT Eligible	0.2743***	0.2612***	0.2947***
	[0.0131]	[0.0250]	[0.0109]
N	68,884	33,754	26,386
Effect size	27.4%	26.1%	29.5%
F-statistic	440	235	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 *Familias en Acción*, 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.