The Impact of Early-Life Shocks on Adult Welfare in Brazil: Questions of Measurement and Timing

Dylan Fitz and Riley League

Lawrence University, Appleton, WI & Duke University, Durham, NC*

November 2019

Abstract

Recent literature provides evidence that income shocks early in life can have long-run consequences on adult welfare. Rural Brazil frequently suffers from rainfall variations that negatively impact vulnerable households, who often lack the means for coping with these events. This paper evaluates how early-life rainfall shocks influence adult health and socioeconomic outcomes in Brazil. We find evidence that several critical periods can produce long-run consequences. Using rainfall deviations, our two most robust results are that greater rainfall in utero negatively impacts adult incomes (finding that a one standard deviation increase in rainfall causes adult incomes to fall by 7-10 percent) and that greater rainfall in the second and third years of life improve adult health (increasing body mass index by 0.16). However, our results depend crucially on our choices regarding two features. First, our results differ across two common measures of critical periods, which are used to define shocks relative to the timing of one's birth. Second, the way rainfall variation is measured also matters, with use of an extreme weather indicator suggesting heterogeneous effects by gender, with extreme weather negatively impacting women's health (both before and after birth) but positively affecting several men's outcomes (both before and after birth). We find some evidence that mortality selection may drive some of these results. This paper provides further evidence that early-life shocks (from in utero through the third year of life) can cause long-run consequences, but also suggests that more attention should be paid to the specific measurement and timing of rainfall shocks. Keywords: health production; education; gender; rainfall; critical periods; Brazil. JEL codes: I12, J16, O15.

*Corresponding author: Dylan Fitz, Lawrence University Economics Department, 711 E. Boldt Way, Appleton, WI, 54911. Email address: dylan.b.fitz@lawrence.edu. Riley League, Graduate Student, Duke University Economics Department. We would like to thank Davidson College for financial assistance in support of this project. This paper benefitted from feedback and suggestions from several referees. Declarations of interest: none.

1 Introduction

Rural populations often rely heavily on rainfall for their incomes while lacking adequate opportunities to minimize the risk resulting from variable rainfall. In particular, Brazil's highly unequal land distribution means that many landless individuals and small farmers remain particularly vulnerable, depending on rainfall for both their own production and for labor earnings in the agricultural sector. In this context, rainfall variations can reduce agricultural earnings and increase the risk of disease, both of which can negatively impact health and welfare in the short-run. Without insurance, the vagaries of the rainfall and the consequences of regular floods and droughts are a recurring theme in Brazilian life and the culture of rural areas. In his famous discussion of the semiarid area of Northeastern Brazil, Euclides da Cunha writes that: "At the height of the droughts they are, positively, a desert, but, when the droughts are not prolonged to a point where they occasion a painful exodus, man may be seen struggling like the trees, with the aid of those reserve forces which he has stored up in the days of plenty." In short, this paper studies the long-term impact of building up or depleting these reserve forces early in life.

There is growing evidence that these short-run shocks also have long-run consequences, especially for those that experience significant shocks in utero or early in life (Almond and Currie, 2011). However, there is little consensus about which periods are critical and which groups are most susceptible to negative shocks (Currie and Vogl, 2013). For example, in utero exposure to a flu pandemic negatively impacted a range of adult health and socioeconomic outcomes in the United States (Almond, 2006) and Brazil (Nelson, 2010). Studying the impact of war on individuals, Akresh et al. [2012] also find that in utero exposure is the most important critical period. In contrast, Maccini and Yang [2009] find that rainfall during and after the season of birth matters for women (but not men) while both Glewwe and King [2001] and Alderman et al. [2006] find that the second year is a critical period. Shah and Steinberg [2017] find that more early-life rainfall improves childhood educational outcomes, with the most important critical periods including ages 0-2 while ages 3-4 matter but to a lesser degree. Thus, while many individual studies find evidence that specific critical periods matter (most commonly in utero, the first year, or the second year), the collective findings fail to reach a consensus about which periods are critical for which groups and in which contexts.

In this paper, we evaluate the impact of exogenous early-life rainfall shocks on adult health and socioeconomic outcomes in rural Brazil. We evaluate rainfall variations during several potential critical periods around the year of birth and evaluate how these events impact individuals later in life. Our analysis uses men and women that were born between 1940 and 1979 in rural areas in both the Southeast and Northeast of Brazil. The Northeast in particular contains some of Brazil's deepest and most persistent poverty, which is caused, in part, by variable rainfall, unequal asset ownership, and inadequate infrastructure. While the Southeast experiences higher rainfall levels, its historical rainfall data also exhibits considerable variability. As a result, it provides an opportunity to evaluate the impact of early-life shocks on very vulnerable populations. In order to evaluate these questions, we utilize the 1996-1997 Brazilian Living Standards Measurement Survey (LSMS) alongside detailed monthly rainfall data. The LSMS provides information on adult health and socioeconomic status, which we match to early-life rainfall data using the location and timing of individual births. As an exogenous shock in areas with few ways to mitigate the consequences, rainfall provides a plausible measure of variation in early-life welfare.

We present several key results. First, we find that early-life rainfall variations during certain critical periods impact adult welfare. We find that a one standard deviation increase in rainfall in utero decreases monthly income per capita by 6.8 to 10.4 percent. After birth, greater rainfall positively affects several adult health outcomes, with a one standard deviation increase in rainfall during one's third year of life increasing adult BMI by 0.156 kilograms per meter squared. Greater rainfall during the second year of life similarly increases BMI and reduces the probability of reporting poor health by 0.8 percentage points. Thus, we find that potential critical periods range from the in utero period to the second and third year of life, in contrast with many other papers that find evidence of only one critical period. Collectively, these results indicate that early-life rainfall variations impact adult outcomes in economically meaningful ways.

Our second main result, however, is that these findings depend on two important decisions about how early-life conditions are measured. First, our results differ across two common definitions of critical periods, which determine the timing of shocks relative to the timing of one's birth. One approach (method one) defines the birth year as the month of birth as well as the previous 11 months, thus capturing the period just before conception and in utero, and evaluates additional 12-month periods around the birth year (a measure used, for example, by Thai and Falaris, 2014; Rocha and Soares, 2015; Aguilar and Vicarelli, 2018). Another approach (method two) defines the birth year as the season an individual is born in and the following season (Maccini and Yang, 2009).[1] As discussed below, these measures do not align consistently and the choice of measure matters in our data, given that our findings are not all robust across both of these measures. Second, the way rainfall variations are measured also matters, with results differing between a measure of rainfall deviations (which is monotonically increasing in rainfall) and a binary measure of extreme weather (equal to one if rainfall is more than one standard deviation away from the historical mean in a given region). Among women, extreme weather before birth negatively impacts adult health, lowering BMI by 0.38 to 0.45 kilograms per meter squared and the probability of reporting good or very good health by 4 percentage points. Among men, extreme weather both before and after birth positively impacts a range of adult outcomes. We find evidence that mortality selection among males may partially explain these positive effects.

[1]This definition means that Maccini and Yang's [2009] finding can be interpreted as evidence that critical periods include time in utero or the first months after birth.

Papers evaluating rainfall variations employ a range of measures and the relationship between rainfall and the local economy will differ across various contexts. In the rainfall literature, some papers use deviations from historical means (Maccini and Yang, 2009; Björkman-Nyqvist, 2013), which is more appropriate when the impact of rainfall is monotonic. Other papers use dummy measures capturing extreme rainfall events (Jensen, 2000; Miguel, 2005; Shah and Steinberg, 2017; Adhvaryu et al., 2019), which might include positive and/or negative rainfall shocks depending on the impact of these events in a particular context. Others use a combination of approaches (Rocha and Soares, 2015). We find that the relationship between early-life rainfall and long-run health may even differ within the same sample, with results among men and women being more similar overall when using rainfall deviations but considerably different when using extreme weather indicators. Overall, our conclusions depend on the choice of how to measure both critical periods and early-life rainfall. To highlight one example, Maccini and Yang [2009] find that greater rainfall during and after birth positively impacts women but not men, but our results differ in several important ways. When we use their definition of critical periods and rainfall variation (method two in Tables 2-4), we find that greater rainfall during the birth year negatively impacts adult incomes for both women and men (with the result being more robust for men) and that greater rainfall during the third year increases BMI for both men and women. However, these results then change whether we use either a different measure of critical periods (method one in Tables 2-4) or extreme weather shocks (method two in Tables 5-6). While evaluating multiple definitions of critical periods and measures of rainfall variation complicates our analysis, we find it to be important both in our data and as a way to help explain the range of empirical evidence in different studies.

These findings have important policy implications, relating to both Brazil in particular and development policy generally. Growing empirical evidence shows that effective policies early in life can either reduce the impact of negative shocks or significantly improve adult outcomes (see, for example, Hoyne et al., 2016). Given that many households are vulnerable to these temporary shocks that have significant long-run costs, there is a need for policies that better protect households from risk. In particular, these programs are likely to prove to be very cost effective, since they potentially provide both short- and long-run benefits. In Brazil, programs might include increased access to insurance, irrigation, and cash transfers to households.

2 Literature Review and Context

Recent literature provides growing evidence that early-life conditions can cause lifelong consequences (Almond and Currie, 2011). While weather shocks can impact urban areas (Cornwell and Inder, 2015; Baez et al., 2017), we focus on rural areas, where rainfall shocks can be one of the most significant negative shocks that households face.[2] Rainfall variation can impact short-run welfare through several channels, which may then produce long-run consequences. First, rainfall determines agricultural yields and wages, which influence household incomes and consumption levels and, in turn, fetal and child health. Early-life child health can persist directly into adulthood or cause latent long-run effects such as increases in obesity and disease (Barker, 1990). However, the relationship between rainfall and agricultural yields is complex, with greater rainfall potentially increasing yields in one region but not another (Galindo, 2009; Skoufias and Vinha, 2013). However, while a slight change in rainfall may increase or decrease yields, extreme weather should decrease yields, whether due to drought or floods (Bobonis, 2009). Second, changes in rainfall impact the disease climate, which influences child health with potential long-run impacts. Again, depending on the specific disease climate, additional rain may increase or decrease health risks. In many cases, reduced rainfall causes water scarcity, which increases the risk of cholera, typhoid fever, diarrhea, and other infections diseases (WHO, 2012). In contrast, across 28 African countries Kudamatsu et al. [2016] find that higher rainfall increases mortality due to malaria. Collectively, given rainfall's potential positive and negative effects on child nutrition and health, it is perhaps unsurprising that studies find mixed evidence linking the two. For example, Skoufias and Vinha [2012] find that positive rainfall shocks negatively impact child health, but that negative rainfall shocks increase child height in several cases. They argue that this result suggests "that on average in rural Mexico weather-related illnesses are more prevalent with increases in precipitation" (p. 68). Also in Mexico, Adhvaryu et al. [2019] find that both negative and positive rainfall shocks reduce incomes. In semiarid parts of Northeastern Brazil, Rocha and Soares [2015] find that higher rainfall deviations reduce infant mortality and that the link is likely not driven by agricultural production, but through access to drinking water and infectious disease rates.

Third, negative short-run shocks may produce long-run outcomes contingent on two contrasting effects: a selection effect (where children with worse health die, thus leaving a healthier population) and scarring (where surviving children have lower health). Bozzoli et al. [2009] develop a model illustrating how, at higher levels of mortality, the selection effect dominates the scarring effect and can produce healthier adults in response to early-life shocks. They find suggestive evidence of this using data from over 40 developing countries, including Brazil. In India, Pathania [2009] finds that in utero drought exposure decreases height among higher caste women but increases height among a lower caste, noting that this could be driven by mortality selection among lower castes. We interpret our results below in light of these findings and potential channels linking early-life shocks to adult welfare.

While there is persuasive evidence that early-life conditions have long-run impacts, there is no consensus about

[2] While this paper focuses on rainfall shocks, other studies show that many types of early-life shocks have long-term consequences, including war (Alderman et al., 2006, Akresh et al., 2012, Bundervoet and Fransen, 2018), fasting (Almond and Mazumder, 2011, Karimi and Basu, 2018), disease (Almond, 2006, Bleakley, 2007, Barreca, 2010, Bleakley, 2010, Cutler et al., 2010, Nelson, 2010, Portrait et al., 2017), famine (Lindeboom et al., 2010), economic conditions (Van den Berg et al., 2006), and lack of nutrition (Field et al., 2009), among others.

which critical periods matter and which individuals are most affected in which contexts. Many studies find that in utero shocks significantly impact not only birth outcomes (Rocha and Soares, 2015), but also health and education among both children (Akresh et al., 2012; Thai and Falaris, 2014; Kumar et al., 2016; Aguilar and Vicarelli, 2018; Rosales-Rueda, 2018; Adhvaryu et al., 2019) and adults (Almond, 2006; Field et al., 2009; Nelson, 2010; Bundervoet and Fransen, 2018). Dobbing [1976] hypothesized that the final term of pregnancy and the first six months of life are the most critical periods for brain growth and, as a result, negative shocks at these times may have the largest long-term impacts on cognitive development. This finding is supported empirically by Maccini and Yang [2009], who find that adverse rainfall shocks during the year that includes the season of birth and the following season negatively impact health, education, and labor market outcomes among Indonesian women. In contrast, other findings indicate that the second and third year of life are most critical for explaining cognitive and health development. Glewwe and King [2001] find that the first six months are not significant, but the second year of life is significant. Alderman et al. [2006] find that droughts during the second and third year of life negatively impact childhood health and adult outcomes. Hoddinott and Kinsey [2001] find that drought exposure during the second year reduces child growth, but that later exposure does not. Recently, Shah and Steinberg [2017] find that shocks from ages 0-4 negatively impact child education, but that the most likely critical periods involve ages 0-2.

In addition to differences in the timing of shocks, individuals may be differentially affected by negative shocks. For example, Maccini and Yang [2009] find that women are affected while men are not. This paper adds to the literature by testing for various critical periods among both men and women in rural Brazil and comparing distinct ways of measuring critical periods and early-life rainfall variations.

This is a particularly important topic to analyze in rural Brazil, and we focus on households born in rural areas in both the Northeast and the Southeast. With extremely unequal land ownership, many farmers rely on rainfall for their agricultural production and the prevalence of agricultural wage labor means that rainfall will impact incomes and consumption for many rural households. Even as recently as 2006, irrigation rates among family farms remain low at 5.26% in the Northeast and 12.12% in the Southeast (Medina et al., 2015). Because in rural Brazil there is both heavy dependence on rainfall as well as frequent droughts, it is important to better understand the impact of rainfall variation in this context. During our period of study, droughts occurred in the Northeast, for example, in 1941–1944, 1951–53, 1958, 1966, 1970, 1976, and 1979–1981 (Marengo et al., 2017). Many of these droughts have devastating immediate effects on the region. The 1979-1981 drought caused more than a "70% reduction in production of rice, beans, and cotton, and prices went up by 100%" and then the 1982-1983 drought caused "a decrease of 80% in livestock" (Marengo et al., 2017). These severe droughts along with regular rainfall variation are major determinants of rural incomes, consumption, and health, and this paper evaluates the long-run effects of this rainfall variation on adult health and socioeconomic outcomes.

3 Data

This paper integrates survey data (including information about adult education, health, and incomes as well as the timing and location of birth) with detailed historical rainfall data. By combining rich data sets and creating variables measuring early-life rainfall shocks and adult outcomes, we are able to evaluate the long-run impact of adverse early-life shocks.

3.1 Rainfall Data

Weather data comes from the Terrestrial Air Temperature and Precipitation: 1900-2014 Gridded Monthly Time Series, Version 4.01 (Willmott and Matsuura, 2015). This dataset provides monthly average temperature and monthly total precipitation for 0.5 degree by 0.5 degree squares worldwide, centered on 0.25 and 0.75 degree nodes. The data is created using spatial interpolation of the weather stations within the square surrounding each node, with an average of 20 stations. We matched the weather data to municipalities by locating each municipality's centroid within the 0.5 degree grid of nodes. The weather data for the four nodes surrounding the municipality are then averaged, weighting each node by its linear distance from the municipality's centroid.[3] We then construct a state-level rainfall measure by taking a simple average of the rainfall recorded at each node in the state.[4][5]

The rainy and dry seasons are calculated using the same method for both municipal- and state-level weather data. The rainy season is calculated by finding the block of four-consecutive months with the highest average rainfall for each state or municipality. The dry season is the eight months that are not a part of the rainy season.

[3] If the municipality was located at the exact same latitude (longitude) as the nearest nodes, then a weighted average of the nodes directly to the east and west (north and south) was used. If, as was the case for a select number of municipalities, the centroid was at the same geographic coordinate as a node, then the data of that node was used exclusively. Because the weather dataset was created using weather stations, there is only data for nodes above land. This means that for many municipalities, especially those along the coast, there is not data for all four nodes surrounding the municipality. In the case that data for one or two of the surrounding nodes was missing, a weighted average of the remaining nodes was used. In the case that three of the surrounding nodes were missing, the data from the remaining node was used exclusively. There were three municipalities for which all four surrounding nodes were missing (Tavares and Mostardas in the Southeast and Fernando de Noronha in the Northeast). There were also a number of municipalities for which the coordinates of their centroid were unknown.

[4] Many of the nodes are located close to the border between two states, so the data for these nodes relies on weather information from stations in both states. To avoid contaminating the data for one state with rainfall measured in another, the nodes that draw from multiple states are weighted according to the proportion of the square surrounding the node that falls into either state. For example, if a quarter of the square surrounding a node falls into one state and three-quarters of the square fall into the other, then the node will have a quarter the weight of a node whose square is fully within the state for the former state and three-quarters weight for the latter state.

[5] As an unreported robustness check, we construct another state-level rainfall measure by taking a weighted average of the municipality-level rainfall measure for the municipalities in a state with weights corresponding to the geographic size of the municipalities and found that most of the results are robust on this dimension.

With data encompassing such a wide territory with remarkably distinct climates, it is important that different geographic regions be allowed to have different rainy seasons, which our methodology allows for. On the other hand, it is challenging to identify a rainy season length that is appropriate for each state or municipality. Within the Northeast, our data spans all nine states and ranges from wetter Atlantic coastal regions to the drier interior, encompassing a wide range of climates. Similarly in the Southeast, our data spans all four states and a range of climates. Using data for all states from 1900-1979, Figure 1a shows that rainfall is highest during a four-month period from December through March and we use four months as our preferred rainy season length. Figure 1b shows differences between macroregions, with rainfall peaking in March in the Northeast and December in the Southeast. For the Northeast, this is consistent with the evidence in Rocha and Soares [2015], who find that rainfall is highest in March and particularly high from January through April, using a more recent time period. The rainy and dry seasons that we find using our data are quite similar to those found in Rao et al. [2016] and Rao and Hada [1990], who calculate three-month rainy seasons. In unreported robustness checks, we also conduct our analysis using two different measures of rainy season. First, Figure 1a shows that rain is particularly high from January through March. Second, Figure 1b indicates that there may be a four-month rainy season in the Northeast (February through May) and a six-month rainy season in the Southeast (October through March). We implement a robustness check using both a three-month rainy season for the entire sample and separate four- and six-month rainy seasons for states in the Northeast and Southeast, finding that our main results are largely robust to these changes.

3.2 Rainfall Variables

We use the rainfall data to construct several measures of early-life rainfall, aggregating monthly rainfall data into yearly information measured relative to an individual's year and month of birth. We focus on several critical time periods and compare results using two standard methods for measuring critical periods.

In method one, the *before birth* period includes the month of birth and the previous 11 months for any given individual in any location of birth. This provides a measure of rainfall right before conception and in utero, which are potential critical periods for child development (as noted above and supported by Thai and Falaris, 2014; Rocha and Soares, 2015; Aguilar and Vicarelli, 2018). We also evaluate the *first year* of life, which includes one to 12 months after birth. Dobbing [1976] hypothesized that the first six months after birth are an important critical period for cognitive development. The *second year* of life (13 to 24 months after birth) provides another potential critical period for development, as shown by Glewwe and King [2001] and Alderman et al. [2006], and we also evaluate the *third year* of life (25 to 36 months after birth).

In method two, we use the measures utilized by Maccini and Yang [2009], who calculate *birth year* rainfall as the season an individual is born in and the following season. We also measure the rainfall one year *before birth* as well as *one, two, and three years after* an individual's birth year. Maccini and Yang [2009] find evidence that the birth year is the only critical period that determines adult health, education, and wealth, and only among women.

Figure 2 provides a comparison of both methods and shows that they match up differently based on the timing of the rainy season relative to the month of birth. Constructed for an individual born in May of 1952, this figure illustrates method one alongside method two under the scenario where the child is born in the middle of the rainy season (Season Scenario A) and at the end of the dry season (Season Scenario B). For example, the in utero period corresponds to before birth in method one or parts of the before birth and birth year periods in method two, and we interpret these periods as the in utero period to simplify our interpretations below. Both measures are used in the literature and we present both results for comparison.

Given these two methods of measuring critical periods, we then calculate annual *rainfall deviations* for each individual born in any given municipality or state. We define the deviation in rainfall as the natural logarithm of a given year's rainfall minus the natural logarithm of the average annual rainfall in the location of birth, calculated as a moving average over the 40-year period before one's year of birth. As a difference of natural logs, the rainfall deviation measure is interpreted as the percentage deviation from the average annual rainfall in a given location. This variable is commonly used in rainfall studies and captures deviations from the long-run mean. As shown in Figures 3a and 3b, there is an upward trend in annual rainfall in the Northeast (but not the Southeast) and the use of a moving average allows us to compare our early-life rainfall with historical averages relevant in a given location at a specific time in history.

In addition to *rainfall deviations*, we evaluate another commonly used rainfall measure: an indicator measuring whether or not a location experienced *extreme weather* in a given year. Recognizing that both unusually dry and wet years can impact agricultural yields, wages, disease rates, and other short-run outcomes, we define extreme weather to be equal to one if annual rainfall is one standard deviation above or below a given location's 40-year moving average. While some papers evaluate indicators of droughts (Rocha and Soares, 2015) and extremely rainy years (Aguilar and Vicarelli, 2018), our historical data involves both extremely dry and rainy years and we focus on extreme weather in either direction (Miguel, 2005; Bobonis, 2009; Adhvaryu et al., 2019).

As shown in the summary statistics in Table 1, the average deviation in rainfall is close to zero but the standard deviation is quite large and extreme weather is a common occurrence, regardless of the level of aggregation of rainfall or method for calculating critical periods. Given that the standard deviation across our various state-level rainfall deviation measures ranges from 18.4% to 19.4%, we present the magnitude of all our estimates based on conditions when annual rainfall is 19% above the long-run local mean, or roughly a one standard deviation increase for any of our measures.

3.3 LSMS Data

We analyze adult health and socioeconomic outcomes using the 1996-1997 Brazilian Living Standards Measurement (LSMS) Survey, which was implemented by the Brazilian *Instituto Brasileiro de Geografia e Estatística* (IBGE) in conjunction with the World Bank. Between March 1996 and March 1997, 4,944 households were surveyed in the Northeast and Southeast macroregions of Brazil. The survey focused on five geographic zones in the Northeast (including the rural Northeast, the cities of Fortaleza, Recife, and Salvador, and other Northeastern cities) and five geographic zones in the Southeast (the rural Southeast, the cities of Belo Horizonte, Rio de Janeiro, and São Paulo, and other Southeastern cities). While the Southeast macroregion is the wealthiest region of Brazil, the Northeast is historically the poorest macroregion and, at the time of the survey, more than two-thirds of Brazil's population lived in these two regions (Monteiro et al., 2001). Within each of these 10 geographic units, 480 households were randomly selected through a two-stage process: first census tracts from the 1991 Demographic Census were randomly selected and then households were randomly chosen within each sector. In urban areas, eight households were selected from each of 60 census tracts and, in rural areas, 16 households were selected from each of 30 census tracts. Each household was visited twice over a two-week interval in order to collect information on household demographics (including household members, health, education, etc.), quality of life, and income.

We focus our analysis on individuals born in rural areas because rainfall is expected to impact incomes and consumption most significantly in agricultural contexts. We exclude any individuals born before 1940 but use rainfall data starting in 1900, which provides us with a 40-year moving historical average for local rainfall before one's birth. In order to focus on adults, we also exclude any individuals that are under 18 at the time of the survey (thus removing individuals born after 1979). Restricting the observations by only including those born in rural areas leaves 4,077 individuals (out of 10,088 in the overall LSMS).

The LSMS survey asked each individual their state of birth and we use this information for our primary state-level analysis. While this allows us to maintain 4,077 individuals in our study, it requires us to utilize the state-level rainfall measure, which decreases the geographic precision of our rainfall data. While we prefer these state-level results, in a robustness section we also evaluate the more precise municipal rainfall data by focusing on the municipality of birth for a given individual. However, we are only able to determine the municipality of birth for less than half of our sample, since the LSMS asked individuals for their state of birth but then only whether or not they were born in the same municipality that they resided in at the time of the 1996-7 survey. Thus, for individuals that live in a different municipality in 1996-7 than they did at birth, we are unable to determine their precise municipality of birth. When restricting the analysis to individuals born in rural areas for whom we know the exact municipality of birth, we are left with 1,640 individuals in our sample. Concerns about possible selection bias are discussed below. Thus, our two strategies require trade-offs between the size of the LSMS data and the geographic precision of the rainfall data, and we focus on the state-level analysis and present the municipal-level analysis as an extension of our results.

We first evaluate health outcomes, focusing on anthropometric measures and self-reported health. Height and weight were collected for all household members at the time of the interviews using reliable microelectronic scales and portable stadiometers (Monteiro et al., 2001). As outcomes, we evaluate both adult height and body mass index (weight in kilograms divided by height in meters squared). We also analyze two indicator variables measuring whether or not self-reported health was excellent or very good (equal to one if so) and whether it was poor (equal to one if so). Second, we analyze educational outcomes focusing on an indicator for literacy and years of education.[6]

Third, we evaluate income, focusing on whether or not an individual earns positive income, the inverse hyperbolic sine of total individual income, and the inverse hyperbolic sine of per capita household income.[7] Due to the existence of several outliers, we drop individuals in the top and bottom 1% of height, BMI, and income levels from our analysis.

3.4 Summary Statistics

Table 1 provides summary statistics for our state-level analysis, using individuals born in rural areas and our state-level rainfall measures. The average height and BMI are 161.97 centimeters and 23.94 kg/m-squared, and 31 percent

[6]Brazil's educational system has gone through several transformations during the time covered by this data. Before 1971, education consisted of three levels, including primary or elementary school (four years and known as ensino primário), junior high school (four years and known as ginasial or médio 1º ciclo), and senior high school (Colegial or Médio 2º ciclo). After 1971, the classification changed and students progressed through two categories of primary and secondary school. First, primary education (the 1st grau) consisted of the equivalent of both elementary and junior high school and included grades ("series") 1 through 8. Second, secondary school (the 2nd grau) was the equivalent of high school and included grades 9 through 11 (or ensino médio). In 1996, primary education was further separated into into elementary school (ensino fundamental I or grades 1-4) and junior high school (ensino fundamental II or grades 5-8). Given that our data includes children who attended school both before and after the 1971 change, we scale a continuous "years of education" variable to match the common usage of grades. Our measure defines the final year of education completed as (with years of education normalized so that kindergarten is equal to 0): -2 if report no education or nursery school; -1 if report pre-school; 0 if report kindergarten; 1 through 8 for final year completed of either elementary school or junior high school (before 1971) or primary school (1st grau after 1971); 9 through 11 for final year completed of senior high school (before 1971) or secondary school (after 1971); 12 through 15 for years completed of college (more than 4 years counted as four); and 16 if masters/doctoral degrees reported.

[7]The inverse hyperbolic sine function maintains zero values and is interpreted the same way as a log dependent variable. Given the prevalence of observations of zero income, this transformation is superior to a logarithmic transformation.

of individuals report being in excellent or very good health while only 4 percent report poor health. In terms of education, 71 percent of individuals can read and write and there is an average of 4.66 years of education.

This sample is similar to Brazil's rural population generally. Using the Brazilian Demographic Census from 2000, Jonasson and Helfand [2010] find an average age of 36.27 and an average education level of 3.57 years in rural areas, indicating that our sample has slightly above average education levels. Using the Brazilian Agricultural Census of 2006, Medina et al. [2015] find that 27% of the heads of family farms are illiterate, with the rate increasing to 43% in the Northeast but decreasing to 13% in the Southeast. Education is known to increase agricultural yields among farmers (see, for example, Foster and Rosenzweig, 2010) and is also one of the most important indicators of nonfarm labor opportunities and incomes in Brazil (Kageyama and Hoffmann, 2000; Jonasson and Helfand, 2010).

Table 1 also provides summary statistics for our municipal-level analysis, using those individuals born in rural areas and for whom we know the exact municipality of birth. When restricting the analysis to the municipal level, our sample is reduced to 1,640 adults born in rural municipalities and residing in their municipality of birth at the time of the survey.

4 Empirical Strategy

Using the individual-level LSMS data from 1996-7 with the historical rainfall data described above, we are able to estimate the following regression:

$$Y_{ijt} = \alpha + \beta R_{jt} + \eta X_i + \mu_j + \gamma_j TREND + \delta_t + \epsilon_{ijt}$$

where Y_{ijt} is a specific outcome for individual i born in state j and year t. The coefficient of interest is β and it estimates the impact of rainfall (R_{jt} measures either the deviation of rainfall from the long-term mean or an extreme weather indicator), using the critical periods defined above. We control for parental schooling levels as a proxy for childhood socioeconomic status (X_i), including a separate series of indicators for whether individual i's mother and father completed some or all of elementary school, high school, or beyond (with no schooling excluded). While rainfall remains plausibly exogenous, these controls allow us to evaluate the impact of early-life rainfall conditional on rainfall-invariant childhood income levels, proxied for by parental educational attainment that is assumed to be relatively stable through time. Furthermore, we use these controls because households with less educated heads may be more vulnerable to shocks (Skoufias, 2007). We include state fixed effects (μ_j) to control for any potentially unique but time-invariant characteristics of a given state's climate or socioeconomic environment. The state-specific linear time trend ($\gamma_j TREND$) captures time trends specific to each state, thus providing a flexible control for trends occurring in distinct areas. Finally, we include general birth year fixed effects (δ_t) to control for aggregate shocks that impact all regions as well as season of birth fixed effects. All regressions include robust standard errors that are clustered by the state of birth. For the results utilizing the municipality of birth rather than the state of birth, municipalities replace states in the regression.

This regression captures the causal effects of rainfall on adult-life outcomes under plausible assumptions. A primary concern is the potential existence of omitted variables that might be correlated with our rainfall measures and later adult-life outcomes. There is not likely to be omitted variable bias given that our flexible controls include location fixed effects (thus controlling for location-specific and time-invariant trends), location-specific time trends (thus allowing for a different linear time trend in each location), and year fixed effects (thus controlling for common nationwide shocks).

Another concern relates to individual survival into adulthood. If children born during rainfall shocks are less likely to survive, then their absence in the 1997 LSMS survey would cause us to underestimate the deleterious effects of adverse rainfall events on health and socioeconomic outcomes in adulthood. While mortality selection is a concern in the literature (Currie and Vogl, 2013), other studies often find that rainfall variation does not impact the size of cohorts surviving into later years (for example, Maccini and Yang, 2009). We also evaluate the validity of this concern directly using our data and empirical model to test whether early-life rainfall affects cohort size or the likelihood of having any individual born in a given cohort in our sample. As Appendix Table A1 shows, we find some evidence that early-life rainfall has small but detectible effects on survival depending on gender, as discussed below.

Since the LSMS surveyed households in the Northeast and Southeast regions of Brazil, it is possible that households would have migrated out of the sample and that this migration may be correlated with rainfall shocks and socioeconomic variables. Mueller and Osgood [2009] find that rainfall shocks cause some households to migrate, but that, while the Northeast is the main source of internal migrants in Brazil, most households that leave rural areas in the Northeast migrate to urban areas either in the Northeast or the Southeast. They also show that most rural Southeastern households migrate within the Southeast. As a result, while households may migrate from rural areas as a means of coping with risk, they tend to remain within the range of the LSMS survey, which included these major urban areas.

Another potential challenge to our identification is that if parents select whether children are born during the wet or dry season, then children may systematically differ by their season of birth. We find no systematic pattern in cohort sizes across birth months and our sample is distributed across seasons as would be expected with no selection from strategic fertility decision. Furthermore, in unreported tests we find that parental education levels are not significant predictors of the season of birth.

5 Results

5.1 State-Level Rainfall Analysis

We present our results below, with each table displaying coefficients estimating the impact of rainfall using both of the methods for defining critical periods described above. We first focus on the impact of early-life shocks as measured by rainfall deviations, which measure the percentage deviation from the average annual rainfall in a given location. Second, we explore the impact of early-life shocks using an indicator for extreme weather, equal to one if annual rainfall is at least one standard deviation above or below the moving historical average in a given location.

Rainfall Deviations

Table 2 evaluates the impact of early-life rainfall deviations on adult health, education, and incomes. Our first overall finding is that greater rainfall in utero produces several negative impacts. Focusing on the before birth period, exposure to rainfall 19 percent – or roughly one standard deviation – above average causes the likelihood of reporting poor health to increase by 0.4 percentage points (method two, column 5) and it causes per capita household income to fall by 6.8 percent (method one, column 9). Considering rainfall during the birth year period (method 2), which corresponds to parts of the in utero period, we find that a one standard deviation increase in rainfall causes per capita household income to fall by 10.4 percent. Evidence of similar results using birth year in method two and before birth in method one may be due to the importance of trimesters. As seen in Figure 2, these two measures are most likely to overlap during the third trimester and several papers find this trimester to be critical (Deschênes et al., 2009; Andalón et al., 2016; Hoyne et al., 2016), although the first two trimesters are also significant (Deschênes et al., 2009; Almond and Mazumder, 2011; Andalón et al., 2016). Additionally, the likelihood of being literate increases by 1.4 percentage points (method 2, column 5). While many of the outcomes are not significant, the final column presents the p-value for a joint significance test on each rainfall measure across all nine outcomes. Other than the third year in method one, there is strong evidence that each rainfall measure has an impact on adult welfare.

Our second overall finding is that greater rainfall during the second or third year of life has a small but detectible positive impact on adult health. An individual who experiences rainfall 19 percent above average during their third year attains an adult BMI that is 0.156 units higher (method two, column 2). A similar one standard deviation increase in rainfall during the second year of life increases BMI by 0.174 units and reduces the probability of reporting poor health by 0.8 percentage points. Given that the mean value for BMI is over 23 and the standard deviation is over 3, these estimated effects are not huge, but they are also not implausibly large.

Next we disaggregate our results by gender. Table 3 presents our results for women, for whom we find that greater rainfall before and around birth negatively impacts adult incomes while greater rainfall during the second and third year causes mixed impacts on health. Specifically, a one standard deviation increase in rainfall before birth reduces the likelihood of earning positive income by 2.8 percentage points and lowers total individual income by 13.1 percent (method one, columns 7 and 8). A similar rainfall increase during the birth year decreases per capita household income by 10.8 percent (method two, column 9) and during the first year decreases the likelihood of earning positive income by 1.6 percentage points. Focusing on health outcomes, a one standard deviation increase in second year rainfall raises BMI by 0.196 units but decreases the likelihood of reporting good health by 1.3 percentage points (method one, columns 2 and 3). During the third year, a similar increase in rainfall may decrease or increase BMI, with different results using both methods.

Among men, Table 4 presents more consistent and significant evidence that greater rainfall around birth reduces adult incomes while greater rainfall during the second and third year of life improves health. Greater rainfall during the first year reduces the likelihood of earning positive income and per capita household income (method one, columns 7 and 9). This period often corresponds to the birth year in method two, where we see strong evidence that a one standard deviation increase in birth year rainfall reduces the likelihood of earning positive income (by 2.0 percentage points), total individual income (by 15.8 percent), and per capita household income (by 12.7 percent). Greater rainfall in the years after birth provides a range of health benefits. Greater rainfall during the first year increases BMI (method two, column 2) and during the second year it increases the likelihood of reporting good health (method two, column 3). During the third year, a one standard deviation increase in rainfall increases BMI by 0.147 units (method two, column 2) and the likelihood of reporting good health by 3.4 percentage points (method one, column 3). Again, the joint significance tests provide strong evidence that early-life rainfall deviations significantly impact adult welfare.

Generally, we find evidence that greater rainfall before and during the birth year negatively impacts adult incomes while greater rainfall during the second and third year of life improves health. In unreported robustness checks, we show that Tables 2-4 are very robust to two alternative measures of rainy seasons. Furthermore, while height and educational outcomes peak for most individuals by age 18, they may continue to evolve even into the mid-20s. In unreported robustness checks, we find that Tables 3 and 4 are generally robust to focusing only on individuals age 25 or older.

The evidence that higher rainfall deviations have negative effects in utero and positive ones during the second and third years poses a puzzle. If higher rainfall does increase agricultural yields, these results could be driven by a simultaneous increase in disease rates that has larger effects in utero and immediately after birth, when children may be more vulnerable to disease. Alternatively, higher rainfall may increase survival rates in utero among less healthy babies, resulting in larger cohorts with lower adult outcomes. As shown in Appendix Table A1, we find little evidence that rainfall deviations before birth and during the birth year influence our cohort size and likelihood of observing births. Among men, the before birth coefficient is significantly positive (column 6), but it is only weakly significant. However, the sign of the effect is consistent with the results from Rocha and Soares [2015], who find that higher in utero rainfall decreases infant mortality. If true, then mortality selection may bias our results among males downward. Furthermore, for women we find that higher rainfall deviations in the third year after birth increases the cohort size and likelihood of observing births. While Rose [1999] finds that that survival rates among girls are more responsive to rainfall, we find some effects among both genders. This suggests that survivorship bias may influence our findings among each gender.

Extreme Weather

As seen in Figures 3a and 3b, both Northeast and Southeast Brazil experience annual rainfall levels that are both much higher and much lower than normal, and, as argued above, both extremes can impact agricultural earnings as well as the disease environment. In this section, we consider this possibility by evaluating an extreme weather indicator that is equal to one if rainfall is more than one standard deviation away from the moving 40-year historical average for a given location.

Tables 5 (females) and 6 (males) evaluate the impact of extreme weather during the same combination of critical periods used above and display a combination of both negative and positive impacts on adult welfare. Focusing on women in Table 5, extreme weather negatively impacts a range of health outcomes over a range of critical periods. First, extreme weather before birth reduces BMI by 0.381 to 0.449 (method one and method two) and reduces the probability of reporting good health by 4 percentage points. Extreme weather during the first year reduces the likelihood of reporting good health by 3.9 percentage points (method two) and during the third year it reduces height by 0.656 centimeters (method one). However, we see no evidence that educational outcomes are affected and only one significant impact on any measure of income.

Table 6 evaluates the impact of extreme weather on men and, overall, we see evidence of positive impacts across a range of outcomes across health, education, and incomes. Extreme weather in utero matters in a variety of ways. Between the two methods, the before birth period is found to increase BMI, years of education, and two measures of income. Extreme weather during the birth year increases literacy and schooling and increases the likelihood of reporting good health (method two). While extreme weather during the first year is found to decrease height, it also decreases the likelihood of reporting poor health (both method one). Extreme weather during the second year increases the likelihood of reporting good health (method one) and during the third year it increases BMI (method two) and decreases the likelihood of reporting poor health (method one).

The evidence that extreme weather negatively impacts women but positively impacts men is also surprising. One potential explanation is that extreme weather causes higher rates of mortality among boys but lower rates of mortality among girls. We find that extreme weather during the third year reduces our male cohort size and likelihood of observing male births (Appendix Table A1, method one) while having the opposite effects among women (Appendix Table A1, method two). Mortality selection could leave a healthier cohort of males that would bias our estimates upward and might help explain the positive results among males. However, we also find that extreme weather during the first year increases cohort size and the likelihood of births among males, which may bias our results downward. Among males, we find that extreme weather during the first year causes several negative effects, but positive ones during the third year, results consistent with potential mortality selection based on these results. While intrahousehold gender discrimination may explain why women are more negatively impacted than men, it does not explain why men might benefit from extreme weather.

5.2 Municipal-Level Rainfall Analysis

The preceding results utilize state-level rainfall measures; we now turn to our municipal-level analysis which, as discussed above, reduces our sample size but provides more geographically precise rainfall measures. We next present these results, focusing on robustness checks that evaluate the strength of our evidence. In particular, we address concerns about migration and calculate bounds on our estimates using various extreme assumptions. Given the prevalence of rainfall deviations in the literature (see, for example, Maccini and Yang, 2009; Björkman-Nyqvist, 2013; Rocha and Soares, 2015) and to focus our analysis, we evaluate only the rainfall deviations measure.

Migration

A potential identification concern about our municipal-level analysis relates to migration away from the municipality of birth. While we have information on the state of birth for all individuals in the sample, we only know the municipality of birth for those who were still living in their birth municipality at the time of the LSMS survey. Among respondents born in rural areas, those who have migrated away from their municipalities of birth tend to have better outcomes than those who have not.[8] That migrants tend to have better adult outcomes across a variety of measures could be somewhat worrying for our identification strategy given that we exclude migrants from our municipal-level analysis. If the decision to migrate is endogenous, then our estimates of the effects of early-life rainfall would be inconsistent. Specifically, if lower early-life rainfall is correlated with a lower probability of migration later in life, then our coefficients would be biased upward and we would be more likely to incorrectly conclude that rainfall positively affects later-life outcomes.

As evidence that this is not the case, we can examine the differences between migrants and non-migrants in early-life rainfall as measured at the state level. Because we have data on each respondent's state of birth, we are able to determine whether migrants tend to be exposed to more or less rainfall in their early life. Appendix Table A2 reports results using our empirical strategy discussed above to test for an effect of early-life rainfall on the probability of an individual migrating away from the municipality of birth. We find some evidence that in utero rainfall increases the probability of migrating (methods one and two), particularly for women (method one). This, combined with the evidence that migrants have better later life outcomes, indicates that our estimate can be seen as a lower bound on the true estimate. We find no evidence of rainfall after birth affecting the the probability of migration using the full relevant sample (column 1) or limiting the sample to only female (columns 2) or male (columns 3) observations.

Bounds

The main cost to analyzing the municipal-level rainfall is that our sample size falls by more than half, since for migrants we only know the state of birth and not the municipality of birth. In order to attempt to maintain these migrants in our municipal-level analysis, we present additional results based on a series of strong assumptions that provide us with lower and upper bounds on the effects of early-life rainfall deviations. Our bounds are similar to those employed by Akresh et al. [2016], who evaluate the impact of early-life exposure to conflict in Ethiopia and Eritrea. Similarly, their data includes the region (but not the municipality) that individuals migrated from and they make strong assumptions that any children who migrated during the conflict lived at the conflict site itself.

[8] In unreported results, we find that migrants tend to be heavier and more educated (both in terms of literacy and years of education) and to earn higher incomes.

We employ similarly strong assumptions that migrants faced the highest and lowest observed state-level rainfall for each of the critical periods, thus producing a complete range of assumptions about the rainfall individuals could have been exposed to. That is, rather than excluding individuals who have migrated from their municipality of birth, we include them by making various assumptions about the early-life rainfall they may have been exposed to, and we report only the maximum and minimum estimates obtained for each coefficient. In this way, we provide an upper and lower bound on the correct estimate when all individuals are included. The assumptions we use to bound the results are that migrants were born in the municipality within their state of birth that was exposed to either the highest or the lowest deviation from the mean level of rainfall in each of the years being studied. This means that using method one, we use a set of eight different assumptions: that migrants were born in the municipality with the most or least rainfall in the year before their birth, the municipality with the most or least rainfall 1 to 12 months after their birth, and so on. Using method two, we use the corresponding set of ten different assumptions.

Results

Tables 7, 8a, and 8b present our municipal-level results using only individuals who live in the their municipality of birth (Table 7) and then we add our bounds to evaluate health and education outcomes (8a) and incomes (8b). Without including migrants, we find evidence that greater in utero rainfall is beneficial, in contrast with our state-level results. Greater rainfall reduces the likelihood of reporting poor health for rainfall during the before birth period (method one) and increases per capita household income for the birth year period (method two). We find some positive and some negative impacts of rainfall during the second and third year. Overall, these results suffer from larger standard errors and several of these results are only weakly significant.

When including migrants, we don't find any cases where both the lower and upper bounds are significant, but we do find cases where even under extreme assumptions about migrants the sign of the estimate is unaffected. Focusing on in utero rainfall, the lower bounds suggest that higher before birth rainfall could affect health negatively (height and BMI in method one) or positively (probability of reporting poor health in method one). A similarly mixed result links before birth rainfall and per capita household income. We see some evidence that greater birth year rainfall is beneficial, increasing height and individual income (method two). However, while both bounds have the same sign, the fact that they are not both statistically significant prevents us from confirming any of these effects. Similarly for second and third year rainfall, we see several positive impacts on health and incomes (alongside a few negative ones), but the bounds do not allow us to confirm the effects as positive or negative. Because migrants comprise over half of our sample in Tables 8a and 8b, we may find few significant results due to the measurement error introduced by the strong assumptions driving our bounds analysis.

In unreported results, we also disaggregate these effects by gender, but with the smaller sample sizes we again suffer from large standard errors and the lower and upper bounds do not allow us to confirm effects as positive or negative at both extremes.

6 Conclusion

This paper evaluates how early-life conditions (measured by rainfall variations in rural areas) influence adult welfare, focusing on health, education, and income. Given the limited ability for many rural households to cope with changes in rainfall, these measures represent shocks to agricultural incomes, health, and short-term welfare. With recent literature suggesting that shocks during critical periods can have long-run consequences but no consensus about which periods are in fact critical, this paper evaluates several potential critical periods focusing on particularly vulnerable populations in high-risk rural areas of Brazil.

Our primary finding is that early-life conditions significantly impact adult welfare. Using our primary results using rainfall deviations, we find that a one standard deviation increase in rainfall in utero decreases per capita household incomes as adults by 6.8 (using the before birth period from method one) to 10.4 percent (using the birth year period from method two). In contrast, greater rainfall in the years after one's birth is found to improve adult health. Greater rainfall during the second year increases BMI and decreases the likelihood of reporting poor health and a one standard deviation increase in rainfall during the third year increases BMI by 0.156 kilograms per meter squared.

Second, our results depend on how we measure critical periods and rainfall variation. We compare two common ways of measuring critical periods relative to the timing of one's birth, noting that they do not consistently overlap and our results are not generally consistent across both measures. We also compare two ways of measuring rainfall variations – using both monotonically increasing rainfall deviations and an extreme weather indicator – and find that the importance of early-life shocks depends on how rainfall is measured. When we evaluate the effects of extreme weather, we find that shocks negatively impact women's adult health, particularly when the shocks occur in utero or during the first and third years of life. Among men, extreme weather shocks in utero increase adult incomes and education while shocks during the first, second, and third years of life improve several health outcomes. Among men, mortality selection may help explain the positive impact of extreme weather shocks as well as the negative impact of greater in utero rainfall deviations.

Collectively, our findings support a range of studies, which individually tend to find the existence of single critical periods but collectively present evidence across a range of critical periods. A notable exception is Shah and Steinberg

[2017], who find that ages 0-2 are the most critical periods but that ages 3-4 also influence later-life outcomes. As with Almond [2006] and Akresh et al. [2012] (for a flu pandemic and war, respectively), we find that in utero shocks matter. Similarly, Maccini and Yang [2009] find that rainfall during the birth year (a measure evaluated in our method two that can correspond to parts of the in utero period and the first year after birth) impacts adult welfare among women but not men. When using rainfall deviations, we find that greater in utero rainfall decreases adult incomes across several measures. When using extreme weather shocks, we find that in utero shocks negatively impact women's health but increase men's health, education, and incomes. As with Glewwe and King [2001] and Alderman et al. [2006], we find that shocks during the second year have important long-run effects and we also find that the third year matters as well. Across all adults in our sample, a one standard deviation increase in second or third year rainfall increases adult BMI by 0.174 and 0.156 kilograms per meter squared. Extreme weather during the third year decreases height by 0.66 cm among women, but extreme weather during the second and third year improves BMI and self-reported health among men.

Overall, these results support the growing evidence that early-life conditions have long-run consequences and provide further support for policies that help alleviate the negative consequences of short-run shocks. Further research will help to verify which time periods may be critical under which conditions. While many innovative programs have been introduced to these regions since the time period being analyzed (including individuals born from 1940 through 1979), our results have important implications for these policies. The findings suggest that social programs – including insurance, cash transfers, public health investments, and more – likely have even larger benefits than many short-run evaluations are able to calculate. By helping households maintain higher levels of consumption and health during short-run shocks, households will benefit from these programs throughout their lifetimes. This suggests that many of these programs should be expanded and their impacts could be amplified by focusing more explicitly on helping households protect themselves against negative shocks.

Table 1 - Summary Statistics

	State-Level Analysis				Municipal-Level Analysis			
Variables	Mean	Median	St. Dev.	N	Mean	Median	St. Dev.	N
Individual Variables								
Height (centimeters)	161.97	162.00	8.58	3,680	162.41	162.20	8.62	1,503
BMI (kg/m squared)	23.94	23.31	3.84	3,670	23.32	22.59	3.64	1,498
Self-reported health status excellent or very good (=1)	0.31	0	0.46	4,063	0.30	0	0.46	1,629
Self-reported health status poor (=1)	0.04	0	0.20	4,063	0.04	0	0.20	1,629
Literate (=1 if can read and write)	0.71	1	0.45	4,077	0.66	1	0.47	1,640
Years of education	4.66	4	3.45	3,267	4.06	4	3.17	1,268
Positive total income (=1 if positive)	0.51	1	0.50	4,077	0.43	0	0.49	1,640
Total individual income	179.40	9.40	436.78	4,052	141.71	0.00	391.28	1,637
Total individual income (IHS)	2.90	2.94	3.01	4,052	2.39	0.00	2.91	1,637
Per capita household income (IHS)	5.28	5.99	2.61	4,054	4.73	5.57	2.76	1,639
Rainfall Deviation Variables - Method #1								
Before birth	-0.013	-0.005	0.194	4,008	-0.047	-0.019	0.287	1,609
First year	-0.014	-0.009	0.189	4,077	-0.043	-0.019	0.282	1,633
Second year	-0.011	-0.005	0.192	4,077	-0.042	-0.016	0.285	1,633
Third year	-0.009	-0.002	0.184	4,077	-0.038	-0.022	0.286	1,633
Extreme Weather Indicator Variables - Method #1								
Before birth	0.24	0	0.43	4,077	0.33	0	0.47	1,640
First year	0.23	0	0.42	4,077	0.32	0	0.47	1,640
Second year	0.24	0	0.43	4,077	0.33	0	0.47	1,640
Third year	0.23	0	0.42	4,077	0.31	0	0.46	1,640
Rainfall Deviation Variables - Method #2								
Before birth	-0.012	0.001	0.189	4,077	0.002	0.008	0.239	1,633
Birth year	-0.012	-0.004	0.189	4,077	0.006	0.015	0.228	1,633
First year	-0.013	0.002	0.187	4,077	-0.011	-0.001	0.228	1,633
Second year	-0.011	0.003	0.188	4,077	-0.005	0.001	0.240	1,633
Third year	-0.011	0.003	0.185	4,077	-0.016	-0.009	0.237	1,633
Extreme Weather Indicator Variables - Method #2								
Before birth	0.23	0	0.42	4,077	0.31	0	0.46	1,640
Birth year	0.23	0	0.42	4,077	0.32	0	0.47	1,640
First year	0.23	0	0.42	4,077	0.30	0	0.46	1,640
Second year	0.24	0	0.43	4,077	0.32	0	0.47	1,640
Third year	0.23	0	0.42	4,077	0.32	0	0.47	1,640

Notes: Sample restricted to individuals born in rural areas between 1940 and 1979. Municipal-level sample further restricted to individuals whom we can determine the municipality of birth. Continuous outcomes (excluding years of education) in the bottom and top 1% are dropped as outliers.

Table 2 - Effect of Early-Life Rainfall Deviations on Adult Health, Education, and Incomes

	Height (cm)	BMI (kg/m squared)	Self-reported health excellent or very good (=1)	Self-reported health poor (=1)	Literate (=1)	Years of Education	Positive total income (=1)	Total Income (IHS)	Per Capita Household Income (IHS)	Joint Significance Test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Rainfall deviation measures (Method 1):										
Before birth	-0.313	-0.475	-0.046	0.010	-0.003	-0.070	-0.081	-0.399	-0.357*	
	[0.830]	[0.383]	[0.042]	[0.014]	[0.061]	[0.480]	[0.049]	[0.273]	[0.197]	0.000
First year	-1.152	0.335	0.013	-0.007	0.044	0.124	-0.066	-0.348	-0.254	
	[0.884]	[0.412]	[0.053]	[0.021]	[0.030]	[0.221]	[0.044]	[0.266]	[0.143]	0.000
Second year	-0.705	0.916*	0.019	-0.042*	-0.049	-0.364	-0.044	-0.296	0.028	
	[0.940]	[0.438]	[0.044]	[0.022]	[0.034]	[0.275]	[0.063]	[0.388]	[0.247]	0.000
Third year	0.138	-0.272	0.055	0.027	-0.007	-0.039	-0.036	-0.104	0.144	
	[0.515]	[0.344]	[0.048]	[0.018]	[0.030]	[0.330]	[0.061]	[0.293]	[0.217]	0.177
Constant	157.033***	26.602***	-0.037	-0.043**	0.548**	-0.473	0.291	1.766	6.072***	
	[3.982]	[2.407]	[0.110]	[0.017]	[0.220]	[0.613]	[0.235]	[1.365]	[0.785]	
Observations	3,596	3,582	3,968	3,968	3,981	3,202	3,981	3,956	3,960	
R-squared	0.094	0.105	0.100	0.058	0.231	0.205	0.072	0.075	0.118	
Log likelihood	-12646	-9709	-2382	999.8	-1963	-8138	-2739	-9823	-9169	
Rainfall deviation measures (Method 2):										
Before birth	0.276	0.064	0.016	0.023**	0.075*	-0.002	-0.037	-0.100	0.057	
	[0.562]	[0.324]	[0.050]	[0.008]	[0.039]	[0.449]	[0.034]	[0.222]	[0.182]	0.000
Birth year	0.064	0.424	-0.008	0.004	-0.045	-0.038	-0.051	-0.361	-0.549***	
	[0.736]	[0.292]	[0.030]	[0.018]	[0.039]	[0.298]	[0.052]	[0.309]	[0.139]	0.000
First year	0.024	0.421	0.032	-0.030	-0.011	-0.371	-0.003	0.010	0.199	
	[0.683]	[0.502]	[0.049]	[0.018]	[0.038]	[0.284]	[0.037]	[0.224]	[0.188]	0.000
Second year	-1.011	0.215	0.027	0.003	-0.001	0.075	-0.084	-0.495	-0.254	
	[0.842]	[0.437]	[0.048]	[0.018]	[0.044]	[0.375]	[0.073]	[0.379]	[0.310]	0.037
Third year	0.813	0.819**	0.025	0.004	-0.066*	-0.412	-0.014	-0.165	0.050	
	[0.960]	[0.290]	[0.028]	[0.016]	[0.037]	[0.404]	[0.026]	[0.151]	[0.202]	0.000
Constant	158.494***	26.053***	-0.017	0.053	0.463***	0.419	0.117*	0.575*	5.358***	
	[0.829]	[0.651]	[0.024]	[0.043]	[0.044]	[0.605]	[0.055]	[0.302]	[0.309]	
Observations	3,656	3,645	4,036	4,036	4,050	3,242	4,050	4,025	4,027	
R-squared	0.095	0.104	0.102	0.056	0.234	0.210	0.073	0.077	0.119	
Log likelihood	-12861	-9877	-2409	960.6	-2003	-8239	-2785	-9988	-9322	

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level. All regressions include birth year fixed effects, season of birth fixed effects, state fixed effects, state-specific linear trends, and controls for parental education. Continuous outcomes (excluding years of education) in the bottom and top 1% are dropped as outliers. Robust standard errors are clustered at the state level and reported in parentheses. The final column presents the p-value for a joint significance test on each rainfall measure across all nine outcomes.

Table 3 - Effect of Early-Life Rainfall Deviations on Adult Health, Education, and Incomes - Females

	Height (cm)	BMI (kg/m squared)	Self-reported health excellent or very good (=1)	Self-reported health poor (=1)	Literate (=1)	Years of Education	Positive Individual Income (=1)	Total Individual Income (IHS)	Per Capita Household Income (IHS)	Joint Significance Test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Rainfall deviation measures (Method 1):										
Before birth	-0.963	-0.238	-0.120*	0.029	-0.048	-0.276	-0.147**	-0.687*	-0.334	
	[0.818]	[0.620]	[0.056]	[0.020]	[0.060]	[0.405]	[0.057]	[0.350]	[0.284]	0.018
First year	-0.677	0.664	0.031	-0.014	0.107**	0.566	-0.020	-0.027	-0.271	
	[1.021]	[0.999]	[0.064]	[0.020]	[0.037]	[0.347]	[0.068]	[0.397]	[0.272]	0.000
Second year	-0.910	1.030*	-0.066*	-0.034	-0.050	-0.065	-0.050	-0.253	0.434	
	[0.953]	[0.532]	[0.033]	[0.027]	[0.034]	[0.510]	[0.058]	[0.331]	[0.320]	0.000
Third year	0.224	-0.808*	-0.049	0.025	-0.057**	-0.725	-0.044	-0.171	0.187	
	[0.887]	[0.413]	[0.063]	[0.024]	[0.023]	[0.419]	[0.076]	[0.347]	[0.259]	0.000
Constant	155.019***	27.979***	-0.222***	0.066***	0.617**	1.222**	0.205	1.477	5.897***	
	[4.242]	[2.833]	[0.070]	[0.021]	[0.220]	[0.494]	[0.226]	[1.372]	[1.104]	
Observations	1,919	1,905	2,048	2,048	2,053	1,654	2,053	2,050	2,041	
R-squared	0.155	0.122	0.119	0.082	0.237	0.212	0.073	0.077	0.146	
Log likelihood	-6132	-5303	-1146	449.4	-957.2	-4210	-1301	-4878	-4722	
Rainfall deviation measures (Method 2):										
Before birth	0.120	0.244	0.056	0.026	0.087	-0.451	-0.055	-0.119	0.141	
	[0.627]	[0.473]	[0.048]	[0.018]	[0.052]	[0.427]	[0.036]	[0.259]	[0.264]	0.066
Birth year	-0.676	0.778	-0.062	0.009	-0.020	0.007	-0.021	-0.050	-0.571**	
	[0.691]	[0.746]	[0.047]	[0.027]	[0.060]	[0.430]	[0.059]	[0.300]	[0.233]	0.000
First year	-1.584	0.202	-0.023	-0.013	-0.044	-0.053	-0.082**	-0.363	0.455	
	[1.080]	[0.729]	[0.063]	[0.028]	[0.044]	[0.547]	[0.037]	[0.207]	[0.345]	0.000
Second year	0.486	0.166	-0.055	-0.010	0.013	-0.117	0.008	0.132	-0.031	
	[0.860]	[0.724]	[0.056]	[0.023]	[0.052]	[0.731]	[0.060]	[0.294]	[0.434]	0.760
Third year	1.419	1.020**	-0.005	0.007	-0.068	-0.366	-0.049	-0.499*	0.004	
	[1.040]	[0.422]	[0.051]	[0.023]	[0.050]	[0.281]	[0.044]	[0.235]	[0.337]	0.000
Constant	152.896***	27.509***	-0.146***	0.142***	0.395***	1.285*	-0.157***	-0.841***	5.211***	
	[0.974]	[0.934]	[0.040]	[0.044]	[0.063]	[0.652]	[0.042]	[0.211]	[0.366]	
Observations	1,950	1,939	2,086	2,086	2,091	1,675	2,091	2,088	2,078	
R-squared	0.157	0.122	0.120	0.077	0.243	0.220	0.073	0.078	0.148	
Log likelihood	-6231	-5393	-1158	436.5	-979.1	-4264	-1320	-4960	-4811	

Notes: Please see the notes for Table 2.

Table 4 - Effect of Early-Life Rainfall Deviations on Adult Health, Education, and Incomes - Males

	Height (cm)	BMI (kg/m squared)	Self-reported health excellent or very good (=1)	Self-reported health poor (=1)	Literate (=1)	Years of Education	Positive Individual Income (=1)	Total Individual Income (IHS)	Per Capita Household Income (IHS)	Joint Significance Test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Rainfall deviation measures (Method 1):										
Before birth	-1.108	-0.573	0.007	-0.018	0.070	0.464	-0.068	-0.423	-0.343	
	[0.962]	[0.364]	[0.065]	[0.023]	[0.079]	[0.562]	[0.048]	[0.388]	[0.381]	0.000
First year	-1.067	-0.174	0.020	-0.010	-0.014	-0.284	-0.090*	-0.544	-0.315*	
	[1.207]	[0.490]	[0.061]	[0.030]	[0.063]	[0.346]	[0.043]	[0.343]	[0.176]	0.000
Second year	-1.205	0.645	0.098	-0.052	-0.040	-0.684	-0.067	-0.546	-0.395	
	[0.933]	[0.475]	[0.095]	[0.033]	[0.035]	[0.431]	[0.097]	[0.612]	[0.383]	0.000
Third year	-0.432	0.520	0.177**	0.023	0.041	0.789**	-0.069	-0.297	0.054	
	[0.861]	[0.569]	[0.081]	[0.029]	[0.059]	[0.331]	[0.072]	[0.379]	[0.253]	0.000
Constant	154.557***	24.037***	0.478	-0.159***	0.099***	-4.333***	0.263	0.895	6.407***	
	[3.799]	[2.378]	[0.302]	[0.023]	[0.029]	[0.377]	[0.339]	[1.578]	[1.376]	
Observations	1,677	1,677	1,920	1,920	1,928	1,548	1,928	1,906	1,919	
R-squared	0.138	0.158	0.111	0.067	0.268	0.245	0.137	0.140	0.122	
Log likelihood	-5501	-4283	-1191	597.8	-943.3	-3871	-1095	-4592	-4409	
Rainfall deviation measures (Method 2):										
Before birth	-0.613	-0.108	-0.027	0.016	0.056	0.543	-0.024	-0.133	0.000	
	[0.612]	[0.607]	[0.074]	[0.019]	[0.103]	[0.827]	[0.051]	[0.372]	[0.335]	0.016
Birth year	0.283	0.059	0.051*	-0.011	-0.042	0.137	-0.106**	-0.830***	-0.667**	
	[1.180]	[0.411]	[0.026]	[0.021]	[0.044]	[0.302]	[0.043]	[0.230]	[0.247]	0.000
First year	-0.956	0.674*	0.065	-0.051	0.042	-0.619	0.001	-0.105	-0.001	
	[1.144]	[0.351]	[0.103]	[0.037]	[0.044]	[0.403]	[0.074]	[0.481]	[0.452]	0.000
Second year	-0.052	0.059	0.138**	0.004	-0.024	0.255	-0.092	-0.639	-0.534*	
	[0.761]	[0.520]	[0.053]	[0.018]	[0.043]	[0.281]	[0.081]	[0.441]	[0.288]	0.000
Third year	1.032	0.776*	0.058	0.002	-0.066	-0.577	0.049	0.362	0.175	
	[1.264]	[0.365]	[0.058]	[0.020]	[0.073]	[0.757]	[0.046]	[0.380]	[0.404]	0.006
Constant	161.877***	24.598***	0.162**	-0.026	0.559***	-0.421	0.432***	2.165***	5.690***	
	[1.252]	[0.628]	[0.063]	[0.061]	[0.065]	[0.897]	[0.087]	[0.544]	[0.409]	
Observations	1,706	1,706	1,950	1,950	1,959	1,567	1,959	1,937	1,949	
R-squared	0.138	0.155	0.110	0.069	0.264	0.245	0.136	0.140	0.123	
Log likelihood	-5601	-4359	-1207	569.2	-967.1	-3921	-1114	-4665	-4471	

Notes: Please see the notes for Table 2.

Table 5 - Effect of Early-Life Extreme Weather on Adult Health, Education, and Incomes - Females

	Height (cm)	BMI (kg/m squared)	Self-reported health excellent or very good (=1)	Self-reported health poor (=1)	Literate (=1)	Years of Education	Positive Individual Income (=1)	Total Individual Income (IHS)	Per Capita Household Income (IHS)	Joint Significance Test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Extreme weather measures (Method 1):										
Before birth	0.128	-0.381**	-0.040**	0.005	-0.002	-0.019	0.010	0.010	-0.043	
	[0.227]	[0.172]	[0.015]	[0.012]	[0.021]	[0.135]	[0.024]	[0.146]	[0.106]	0.000
First year	0.156	-0.308	-0.024	-0.003	0.017	0.057	-0.039	-0.205	0.034	
	[0.382]	[0.215]	[0.030]	[0.013]	[0.024]	[0.130]	[0.030]	[0.174]	[0.160]	0.002
Second year	0.220	-0.129	-0.022	0.010	-0.005	0.029	0.041	0.220	0.112	
	[0.374]	[0.201]	[0.020]	[0.006]	[0.011]	[0.174]	[0.028]	[0.151]	[0.072]	0.000
Third year	-0.656**	-0.074	0.009	-0.002	-0.026	-0.061	0.009	0.041	-0.164	
	[0.250]	[0.200]	[0.024]	[0.011]	[0.026]	[0.267]	[0.020]	[0.130]	[0.110]	0.000
Constant	152.762***	27.827***	-0.082**	0.139***	0.421***	1.344*	-0.159**	-0.790***	5.250***	
	[0.888]	[0.840]	[0.031]	[0.039]	[0.071]	[0.695]	[0.053]	[0.258]	[0.372]	
Observations	1,950	1,939	2,086	2,086	2,091	1,675	2,091	2,088	2,078	
R-squared	0.156	0.122	0.121	0.076	0.241	0.219	0.074	0.078	0.147	
Log likelihood	-6233	-5394	-1158	436.2	-980.9	-4264	-1319	-4959	-4812	
Extreme weather measures (Method 2):										
Before birth	0.114	-0.449*	-0.009	-0.007	0.009	-0.004	0.004	0.064	-0.017	
	[0.231]	[0.219]	[0.020]	[0.008]	[0.025]	[0.230]	[0.021]	[0.132]	[0.137]	0.003
Birth year	-0.153	0.150	0.021	0.014	0.003	0.048	-0.049*	-0.246	-0.126	
	[0.293]	[0.197]	[0.027]	[0.009]	[0.018]	[0.158]	[0.027]	[0.156]	[0.094]	0.000
First year	-0.152	-0.069	-0.039**	0.001	-0.007	0.237	0.005	0.002	-0.139	
	[0.440]	[0.206]	[0.017]	[0.010]	[0.026]	[0.152]	[0.032]	[0.183]	[0.128]	0.000
Second year	-0.150	-0.168	0.031	0.020	0.007	0.013	-0.003	0.029	0.069	
	[0.369]	[0.238]	[0.023]	[0.013]	[0.021]	[0.171]	[0.024]	[0.155]	[0.144]	0.000
Third year	-0.070	0.272	0.019	0.002	-0.003	-0.019	0.027	0.180	0.068	
	[0.372]	[0.198]	[0.017]	[0.015]	[0.028]	[0.139]	[0.019]	[0.105]	[0.112]	0.000
Constant	152.927***	27.410***	-0.144***	0.129**	0.409***	1.247*	-0.140**	-0.782***	5.218***	
	[0.905]	[0.946]	[0.044]	[0.047]	[0.062]	[0.582]	[0.049]	[0.233]	[0.409]	
Observations	1,950	1,939	2,086	2,086	2,091	1,675	2,091	2,088	2,078	
R-squared	0.154	0.123	0.121	0.078	0.241	0.220	0.074	0.079	0.147	
Log likelihood	-6235	-5393	-1157	438.2	-981.7	-4264	-1319	-4959	-4812	

Notes: Please see the notes for Table 2.

Table 6 - Effect of Early-Life Extreme Weather on Adult Health, Education, and Incomes - Males

	Height (cm)	BMI (kg/m squared)	Self-reported health excellent or very good (=1)	Self-reported health poor (=1)	Literate (=1)	Years of Education	Positive Individual Income (=1)	Total Individual Income (IHS)	Per Capita Household Income (IHS)	Joint Significance Test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Extreme weather measures (Method 1):										
Before birth	-0.005	-0.162	0.009	0.006	-0.001	0.222	0.046*	0.351**	0.177	
	[0.297]	[0.171]	[0.024]	[0.007]	[0.018]	[0.165]	[0.023]	[0.147]	[0.126]	0.059
First year	-0.652**	0.016	-0.003	-0.014**	-0.001	-0.058	-0.014	-0.014	-0.121	
	[0.257]	[0.150]	[0.030]	[0.006]	[0.017]	[0.230]	[0.018]	[0.149]	[0.165]	0.000
Second year	-0.123	-0.264	0.045**	-0.006	-0.025	-0.128	0.006	-0.063	-0.141	
	[0.463]	[0.221]	[0.018]	[0.010]	[0.025]	[0.154]	[0.017]	[0.076]	[0.119]	0.000
Third year	-0.379	-0.237	0.012	-0.017*	-0.025	0.187	0.006	-0.018	-0.170	
	[0.390]	[0.194]	[0.018]	[0.009]	[0.022]	[0.163]	[0.035]	[0.197]	[0.117]	0.017
Constant	161.816***	24.823***	0.085	-0.020	0.597***	-0.461	0.380***	1.863***	5.671***	
	[1.374]	[0.603]	[0.059]	[0.057]	[0.079]	[0.716]	[0.070]	[0.444]	[0.379]	
Observations	1,706	1,706	1,950	1,950	1,959	1,567	1,959	1,937	1,949	
R-squared	0.139	0.155	0.108	0.069	0.264	0.244	0.135	0.139	0.122	
Log likelihood	-5601	-4359	-1209	569.5	-967.6	-3922	-1114	-4666	-4471	
Extreme weather measures (Method 2):										
Before birth	-0.005	0.279*	0.001	0.007	0.015	0.324***	0.013	0.044	0.074	
	[0.455]	[0.130]	[0.019]	[0.014]	[0.013]	[0.105]	[0.022]	[0.166]	[0.173]	0.000
Birth year	0.088	0.279	0.060**	-0.014	0.039**	0.333*	0.010	0.091	0.132	
	[0.394]	[0.158]	[0.020]	[0.010]	[0.018]	[0.185]	[0.020]	[0.114]	[0.167]	0.000
First year	-0.347	-0.036	0.027	-0.008	-0.013	0.026	-0.039	-0.271	-0.170	
	[0.337]	[0.171]	[0.030]	[0.007]	[0.014]	[0.239]	[0.028]	[0.189]	[0.140]	0.001
Second year	0.428	-0.073	0.011	0.004	-0.011	0.202	-0.030	-0.237	-0.094	
	[0.375]	[0.157]	[0.032]	[0.012]	[0.028]	[0.147]	[0.020]	[0.160]	[0.100]	0.000
Third year	0.258	0.652***	-0.004	0.007	-0.015	-0.137	-0.025	-0.191	-0.051	
	[0.405]	[0.149]	[0.029]	[0.012]	[0.021]	[0.145]	[0.022]	[0.139]	[0.101]	0.000
Constant	161.513***	24.429***	0.089*	-0.019	0.573***	-0.287	0.461***	2.382***	5.796***	
	[1.145]	[0.648]	[0.045]	[0.060]	[0.081]	[0.753]	[0.075]	[0.453]	[0.418]	
Observations	1,706	1,706	1,950	1,950	1,959	1,567	1,959	1,937	1,949	
R-squared	0.139	0.161	0.109	0.069	0.265	0.246	0.136	0.140	0.122	
Log likelihood	-5601	-4353	-1208	568.7	-966.5	-3920	-1114	-4665	-4472	

Notes: Please see the notes for Table 2.

Table 7 - Effect of Early-Life Rainfall Deviations on Adult Health, Education, and Incomes (Municipal Level)

	Height (cm)	BMI (kg/m squared)	Self-reported health excellent or very good (=1)	Self-reported health poor (=1)	Literate (=1)	Years of Education	Positive total income (=1)	Total Income (IHS)	Per Capita Household Income (IHS)	Joint Significance Test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Rainfall deviation measures (Method 1):										
Before birth	-0.803	-0.747	0.078	-0.058*	-0.028	0.375	-0.044	-0.306	-0.266	
	[1.322]	[0.462]	[0.069]	[0.033]	[0.056]	[0.354]	[0.053]	[0.341]	[0.324]	0.005
First year	-0.200	-0.698	0.012	-0.031	-0.021	-0.248	-0.040	-0.115	-0.141	
	[1.252]	[0.481]	[0.056]	[0.025]	[0.055]	[0.481]	[0.055]	[0.318]	[0.390]	0.565
Second year	1.022	-0.528	0.066	-0.048	0.092*	0.214	0.060	0.480	0.155	
	[1.397]	[0.445]	[0.056]	[0.040]	[0.051]	[0.451]	[0.058]	[0.342]	[0.362]	0.016
Third year	-0.583	0.472	0.051	-0.026	-0.048	-1.320***	-0.002	0.079	0.021	
	[1.230]	[0.491]	[0.062]	[0.026]	[0.047]	[0.418]	[0.059]	[0.318]	[0.324]	0.004
Constant	177.470***	26.964***	-0.132	0.057	0.823**	-10.808***	-0.756***	-0.381	6.920***	
	[10.722]	[3.987]	[0.249]	[0.113]	[0.365]	[3.263]	[0.214]	[1.798]	[2.358]	
Observations	1,455	1,449	1,577	1,577	1,587	1,231	1,587	1,584	1,586	
R-squared	0.272	0.300	0.348	0.330	0.457	0.551	0.275	0.300	0.452	
Log likelihood	-4960	-3676	-674.1	625.4	-578.3	-2670	-880.5	-3663	-3392	
Rainfall deviation measures (Method 2):										
Before birth	-0.270	-0.529	-0.048	-0.003	-0.039	-0.397	0.040	0.103	0.607	
	[1.471]	[0.437]	[0.055]	[0.031]	[0.049]	[0.419]	[0.068]	[0.399]	[0.374]	0.182
Birth year	1.748*	-0.228	-0.006	-0.023	0.042	0.354	0.005	0.261	-0.078	
	[1.045]	[0.547]	[0.058]	[0.024]	[0.059]	[0.417]	[0.076]	[0.405]	[0.360]	0.305
First year	-0.624	-0.706	-0.017	-0.048	0.040	0.120	0.028	0.004	-0.328	
	[1.238]	[0.614]	[0.057]	[0.033]	[0.053]	[0.392]	[0.071]	[0.406]	[0.265]	0.197
Second year	0.559	-0.069	0.006	-0.002	0.038	0.788	-0.012	-0.140	0.416	
	[1.401]	[0.513]	[0.066]	[0.032]	[0.059]	[0.508]	[0.067]	[0.377]	[0.358]	0.553
Third year	-1.159	0.737	0.096**	0.050*	-0.063	-0.084	-0.058	-0.166	-0.286	
	[1.307]	[0.528]	[0.047]	[0.028]	[0.057]	[0.400]	[0.060]	[0.336]	[0.316]	0.007
Constant	177.533***	22.836***	-0.004	0.002	0.716***	-8.828**	-0.428**	0.662	7.399***	
	[5.300]	[1.764]	[0.224]	[0.084]	[0.172]	[3.507]	[0.210]	[1.284]	[1.238]	
Observations	1,476	1,471	1,600	1,600	1,611	1,242	1,611	1,608	1,610	
R-squared	0.280	0.297	0.347	0.338	0.463	0.551	0.270	0.293	0.457	
Log likelihood	-5027	-3732	-682.3	631.9	-585.5	-2694	-898.8	-3723	-3434	

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level. All regressions include birth year fixed effects, season of birth fixed effects, municipality fixed effects, municipality-specific linear trends, and controls for parental education. Continuous outcomes (excluding years of education) in the bottom and top 1% are dropped as outliers. Robust standard errors are clustered at the municipal level and reported in parentheses.

Table 8a - Bounds of Effect of Early-Life Rainfall Deviations on Adult Health and Education (Municipal Level)

	Height (cm)		BMI (kg/m squared)		Self-reported health excellent or very good (=1)		Self-reported health poor (=1)		Literate (=1)		Years of Education	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rainfall deviation measures (Method 1):												
Before birth	**-1.131****	**-0.117**	**-0.787****	**-0.034**	-0.001	0.040	**-0.063****	**-0.005**	-0.063	0.013	-0.155	0.435
	[0.526]	[0.827]	[0.356]	[0.243]	[0.049]	[0.053]	[0.027]	[0.015]	[0.047]	[0.036]	[0.211]	[0.286]
First year	-1.054*	0.465	-0.543	0.175	-0.036	0.020	-0.035*	0.005	-0.015	0.023	-0.165	0.234
	[0.552]	[0.521]	[0.378]	[0.260]	[0.048]	[0.043]	[0.020]	[0.013]	[0.032]	[0.044]	[0.386]	[0.207]
Second year	-0.261	1.255	-0.774**	0.167	-0.003	0.088	-0.055*	0.001	-0.002	0.058	-0.120	0.248
	[0.633]	[1.146]	[0.380]	[0.252]	[0.037]	[0.055]	[0.032]	[0.014]	[0.033]	[0.038]	[0.393]	[0.159]
Third year	-0.306	0.865*	-0.070	0.392	-0.018	0.039	-0.031	0.012	-0.057	0.006	**-0.907*****	**-0.013**
	[0.689]	[0.485]	[0.359]	[0.263]	[0.041]	[0.054]	[0.025]	[0.020]	[0.042]	[0.040]	[0.342]	[0.169]
Constant	**169.134*****	**169.680*****	**28.824*****	**29.173*****	**-0.206*****	**-0.173*****	**-0.304*****	**-0.267*****	**1.102*****	**1.135*****	**3.458*****	**4.033*****
	[1.573]	[1.565]	[0.812]	[0.742]	[0.058]	[0.062]	[0.044]	[0.039]	[0.075]	[0.076]	[0.561]	[0.513]
Observations	3459	3628	3448	3617	3819	4006	3819	4006	3832	4019	3085	3226
R-squared	0.206	0.207	0.225	0.227	0.252	0.260	0.202	0.207	0.361	0.366	0.407	0.410
Log likelihood	-12518	-11928	-9541	-9085	-2028	-1921	1290	1342	-1614	-1492	-7731	-7380
Rainfall deviation measures (Method 2):												
Before birth	-1.435*	0.515	-0.704*	0.307	**-0.075**	**-0.005**	-0.011	0.012	-0.019	0.040	-0.331	0.090
	[0.736]	[0.605]	[0.413]	[0.382]	[0.049]	[0.050]	[0.025]	[0.030]	[0.032]	[0.044]	[0.236]	[0.210]
Birth year	**0.044**	**2.244****	-0.368	0.368	-0.026	0.048	-0.038*	0.009	-0.010	0.071*	-0.102	0.388
	[0.663]	[0.993]	[0.419]	[0.454]	[0.045]	[0.048]	[0.020]	[0.015]	[0.037]	[0.040]	[0.245]	[0.324]
First year	-0.960	0.681	-0.797*	0.008	-0.050	0.001	-0.030	0.001	-0.007	0.068	-0.269	0.167
	[0.693]	[0.912]	[0.480]	[0.291]	[0.050]	[0.054]	[0.026]	[0.017]	[0.035]	[0.045]	[0.230]	[0.305]
Second year	-0.245	1.163**	-0.438	0.264	**-0.069**	**-0.009**	-0.020	0.008	-0.007	0.047	**0.029**	**0.648**
	[0.701]	[0.562]	[0.423]	[0.401]	[0.050]	[0.054]	[0.020]	[0.026]	[0.048]	[0.049]	[0.291]	[0.397]
Third year	-1.107*	0.722	-0.386	0.593	**0.009**	**0.096****	**0.004**	**0.038***	-0.055	0.017	-0.199	0.200
	[0.624]	[0.516]	[0.425]	[0.423]	[0.029]	[0.044]	[0.015]	[0.022]	[0.041]	[0.029]	[0.234]	[0.323]
Constant	**168.547*****	**169.428*****	**28.591*****	**28.872*****	**-0.208*****	**-0.164*****	**-0.316*****	**-0.294*****	**1.095*****	**1.140*****	**3.832*****	**4.104*****
	[1.358]	[1.424]	[0.605]	[0.586]	[0.058]	[0.050]	[0.038]	[0.035]	[0.061]	[0.061]	[0.487]	[0.540]
Observations	3649	3649	3639	3639	4029	4029	4029	4029	4043	4043	3237	3237
R-squared	0.206	0.209	0.224	0.225	0.252	0.253	0.203	0.204	0.363	0.364	0.408	0.409
Log likelihood	-12593	-12587	-9598	-9595	-2037	-2034	1297	1300	-1627	-1625	-7755	-7753

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level. All regressions include birth year fixed effects, season of birth fixed effects, municipality fixed effects, municipality-specific linear trends, and controls for parental education. Continuous outcomes (excluding years of education) in the bottom and top 1% are dropped as outliers. Robust standard errors are clustered at the municipal level and reported in parentheses. The lower and upper bounds are the minimum and maximum estimation obtained under a range of assumptions about the early-life rainfall exposure of individuals who migrated from their munipality of birth. Estimates for which zero is not included within the bounds are bolded.

Table 8b - Bounds of Effect of Early-Life Rainfall Deviations on Adult Income (Municipal Level)

	Positive Individual Income (=1)		Total Individual Income (IHS)		Per Capita Household Income (IHS)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall deviation measures (Method 1):						
Before birth	-0.039	0.017	-0.199	0.105	-0.397*	0.036
	[0.036]	[0.041]	[0.267]	[0.240]	[0.207]	[0.177]
First year	-0.081	0.005	-0.376	0.036	-0.386	0.009
	[0.053]	[0.030]	[0.303]	[0.178]	[0.316]	[0.224]
Second year	**0.018**	**0.086****	**0.108**	**0.512***	**0.044**	**0.393**
	[0.033]	[0.042]	[0.200]	[0.271]	[0.140]	[0.260]
Third year	-0.015	0.014	-0.095	0.098	-0.098	0.309
	[0.036]	[0.043]	[0.199]	[0.268]	[0.166]	[0.228]
Constant	**0.078**	**0.141**	**0.920***	**1.217****	**5.133*****	**5.340*****
	[0.086]	[0.086]	[0.505]	[0.471]	[0.395]	[0.434]
Observations	3832	4019	3807	3994	3809	3996
R-squared	0.193	0.200	0.202	0.209	0.340	0.353
Log likelihood	-2483	-2351	-9616	-9163	-8670	-8226
Rainfall deviation measures (Method 2):						
Before birth	-0.019	0.064	-0.151	0.361	**0.237**	**0.840*****
	[0.041]	[0.059]	[0.242]	[0.361]	[0.177]	[0.307]
Birth year	**0.012**	**0.094**	**0.095**	**0.693****	-0.266	0.408
	[0.044]	[0.061]	[0.242]	[0.334]	[0.304]	[0.303]
First year	-0.027	0.041	-0.189	0.154	-0.445*	0.027
	[0.040]	[0.054]	[0.235]	[0.315]	[0.235]	[0.230]
Second year	-0.015	0.032	-0.100	0.164	**0.041**	**0.588****
	[0.052]	[0.034]	[0.306]	[0.193]	[0.272]	[0.251]
Third year	-0.085	0.018	-0.369	0.128	-0.514**	0.140
	[0.055]	[0.030]	[0.317]	[0.177]	[0.257]	[0.256]
Constant	**0.136***	**0.210*****	**1.106*****	**1.551*****	**5.081*****	**5.452*****
	[0.072]	[0.072]	[0.386]	[0.380]	[0.301]	[0.331]
Observations	4043	4043	4018	4018	4020	4020
R-squared	0.193	0.194	0.203	0.204	0.343	0.345
Log likelihood	-2501	-2498	-9672	-9670	-8716	-8711

Notes: Please see the notes for Table 8a.

Figure 1a: Average Monthly Rainfall, 1900-1979

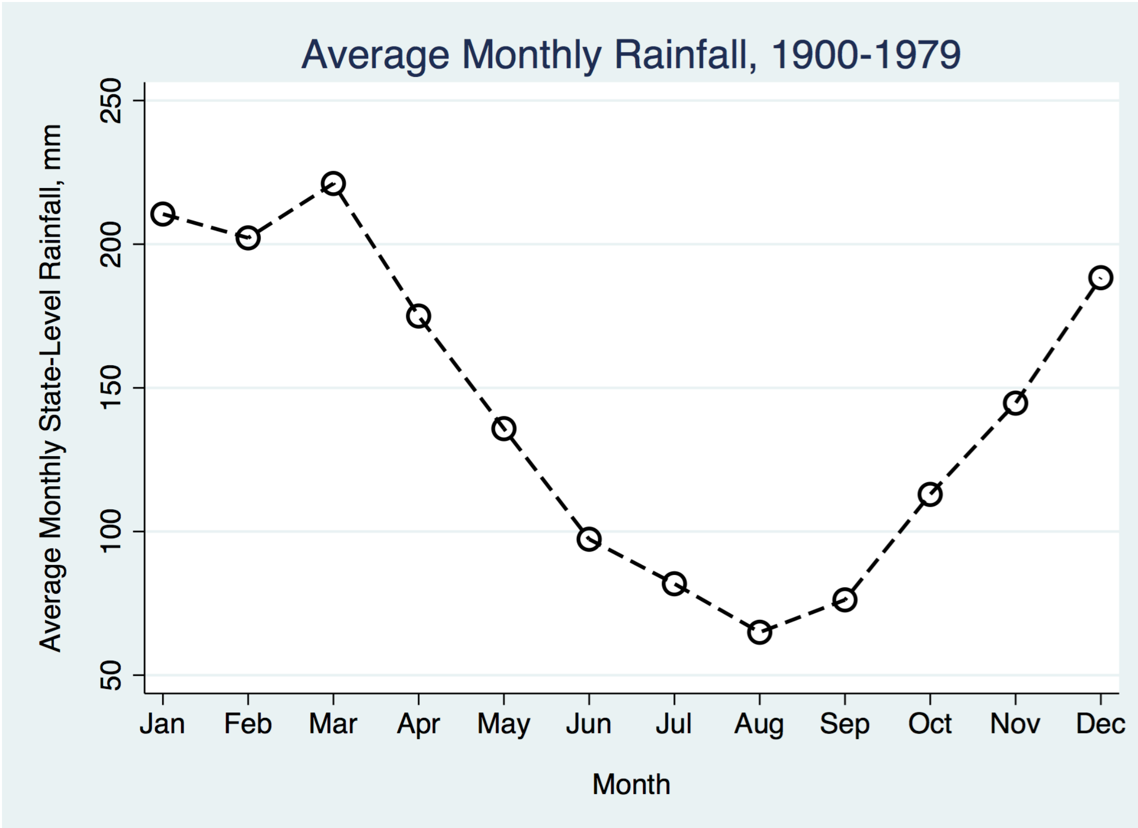


Figure 1b: Average Monthly Rainfall by Region, 1900-1979

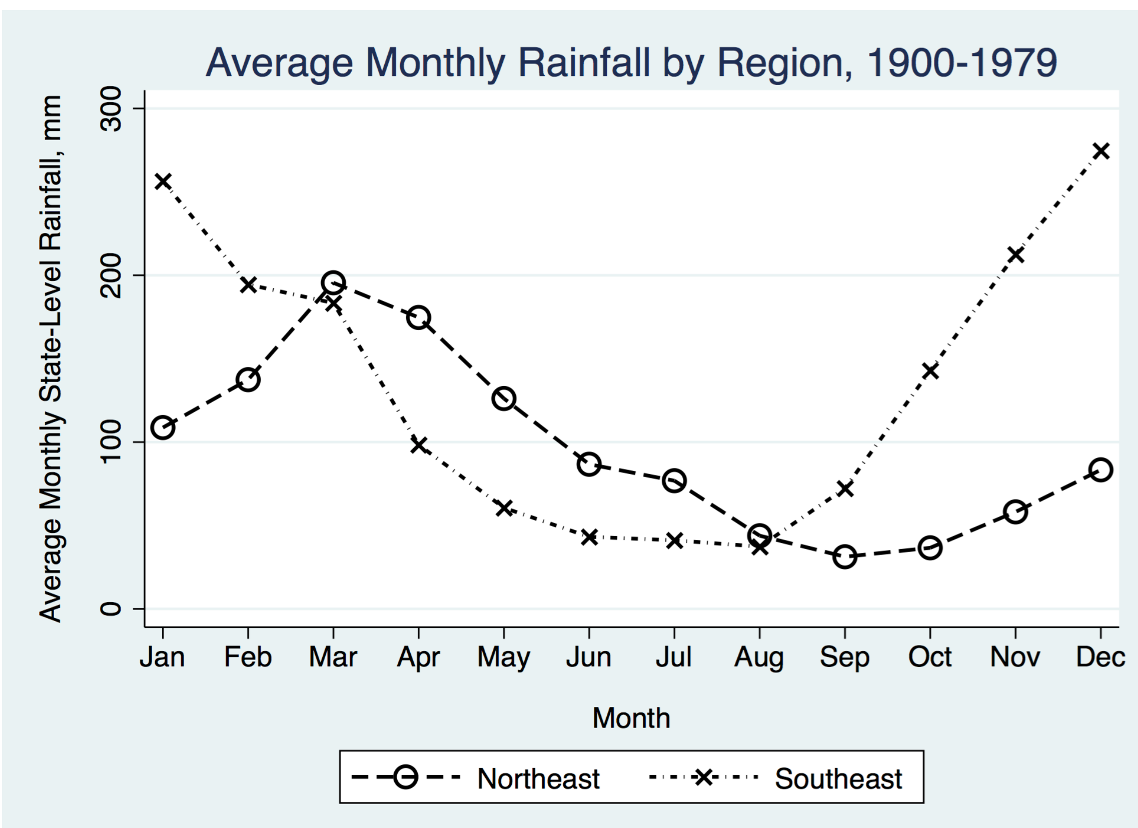


Figure 2 - Comparison of Rainfall Measures

	Year:	Month:		Method 1:	Method 2: Season Scenario A		Method 2: Season Scenario B	
	1950	October			Dry		Dry	Before birth
		November			Dry		Dry	
		December			Dry		Dry	
	1951	January			Dry		Dry	
		February			Dry		Dry	
		March			Dry		Dry	
		April			Rainy	Before birth	Dry	
		May			Rainy		Dry	
		June		Before birth	Rainy		Rainy	
		July			Rainy		Rainy	
		August	In utero		Dry		Rainy	
		September			Dry		Rainy	
		October			Dry		Dry	Birth year
		November			Dry		Dry	
		December			Dry		Dry	
	1952	January			Dry		Dry	
		February			Dry		Dry	
		March			Dry		Dry	
		April			Rainy	Birth year	Dry	
BIRTH DATE:		**May**			Rainy		Dry	
		June		First year	Rainy		Rainy	
		July			Rainy		Rainy	
		August			Dry		Rainy	
		September			Dry		Rainy	
		October			Dry		Dry	First year
		November			Dry		Dry	
		December			Dry		Dry	
	1953	January			Dry		Dry	
		February			Dry		Dry	
		March			Dry		Dry	
		April			Rainy	First year	Dry	
		May			Rainy		Dry	
		June		Second year	Rainy		Rainy	
		July			Rainy		Rainy	
		August			Dry		Rainy	
		September			Dry		Rainy	
		October			Dry		Dry	Second year
		November			Dry		Dry	
		December			Dry		Dry	
	1954	January			Dry		Dry	
		February			Dry		Dry	
		March			Dry		Dry	
		April			Rainy	Second year	Dry	
		May			Rainy		Dry	
		June		Third year	Rainy		Rainy	
		July			Rainy		Rainy	
		August			Dry		Rainy	
		September			Dry		Rainy	
		October			Dry		Dry	Third year
		November			Dry		Dry	
		December			Dry		Dry	
	1955	January			Dry		Dry	
		February			Dry		Dry	
		March			Dry		Dry	
		April			Rainy	Third year	Dry	
		May			Rainy		Dry	
		June			Rainy		Rainy	
		July			Rainy		Rainy	
		August			Dry		Rainy	
		September			Dry		Rainy	
		October			Dry		Dry	
		November			Dry		Dry	
		December			Dry		Dry	
	1956	January			Dry		Dry	
		February			Dry		Dry	
		March			Dry		Dry	

Figure 3a: Average Yearly Rainfall for Northeast Region 1900-1979

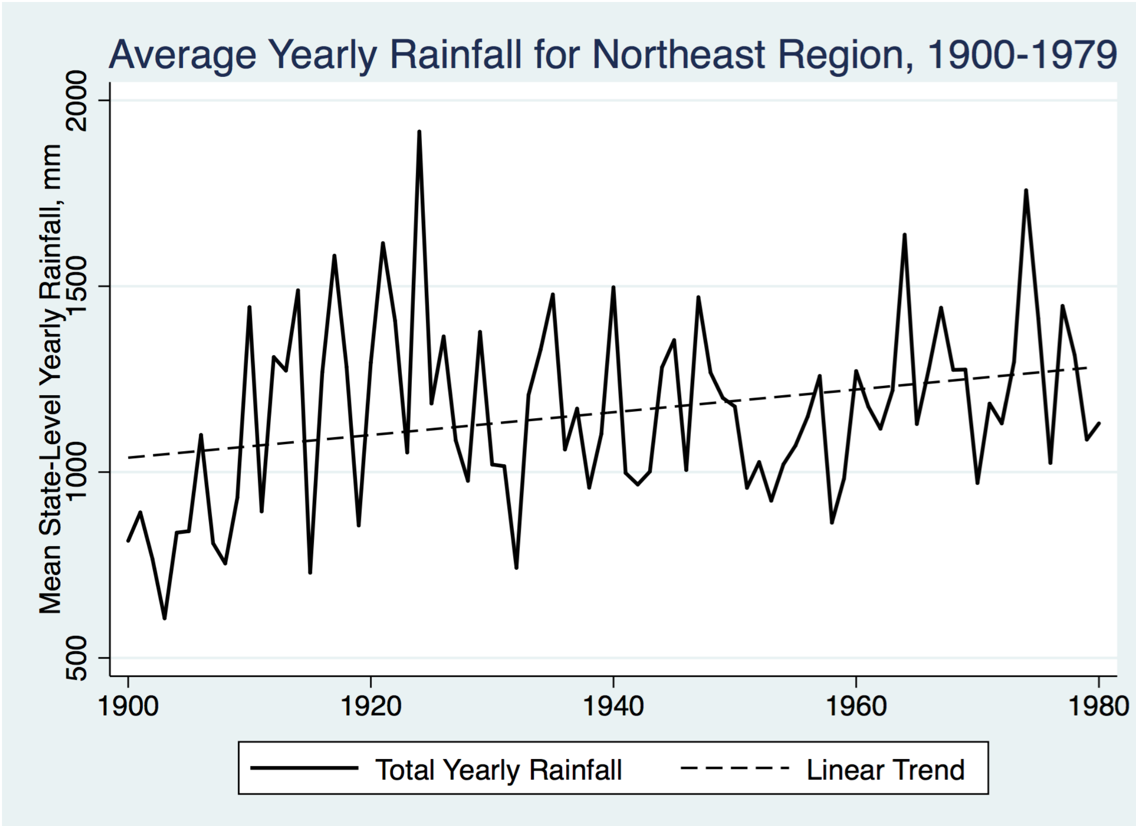
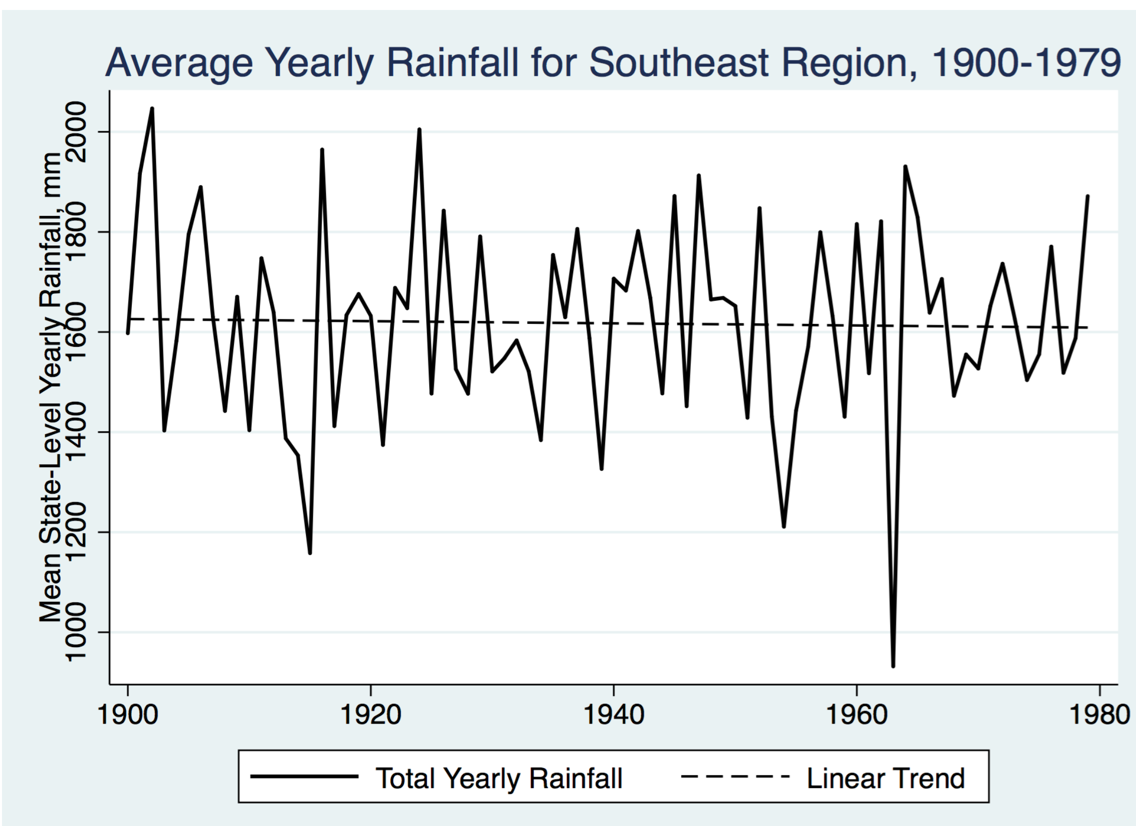


Figure 3b: Average Yearly Rainfall for Southeast Region 1900-1979



Appendix Table A1 - Effect of Early-Life Rainfall on Cohort Size

	Females				Males			
	Rainfall Deviations		Extreme Weather Events		Rainfall Deviations		Extreme Weather Events	
	Cohort Size	Any Births (=1)	Cohort Size	Any Births (=1)	Cohort Size	Any Births (=1)	Cohort Size	Any Births (=1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall measures (Method 1):								
Before birth	0.002	0.004	0.009	0.003	0.039	0.038*	0.002	0.004
	[0.028]	[0.023]	[0.011]	[0.008]	[0.027]	[0.020]	[0.012]	[0.008]
First year	0.017	0.005	0.012	0.011	0.007	-0.000	0.010	0.012
	[0.034]	[0.032]	[0.009]	[0.007]	[0.028]	[0.026]	[0.016]	[0.013]
Second year	-0.024	-0.011	-0.001	0.008	-0.007	-0.010	0.008	0.005
	[0.033]	[0.025]	[0.016]	[0.013]	[0.020]	[0.017]	[0.017]	[0.013]
Third year	0.022	0.025	0.007	0.001	0.006	0.017	-0.018**	-0.013*
	[0.031]	[0.029]	[0.013]	[0.010]	[0.027]	[0.020]	[0.007]	[0.007]
Constant	0.291**	0.328**	0.185***	0.211***	0.297***	0.233**	0.290***	0.218***
	[0.109]	[0.110]	[0.040]	[0.033]	[0.090]	[0.087]	[0.029]	[0.027]
Observations	5,941	5,941	6,084	6,084	5,941	5,941	6,084	6,084
R-squared	0.145	0.117	0.144	0.116	0.149	0.118	0.149	0.088
Log likelihood	-3283	-2118	-3342	-2150	-3517	-2203	-3567	-1976
Rainfall measures (Method 2):								
Before birth	-0.009	-0.007	0.008	0.006	0.018	0.025	0.025	0.018
	[0.026]	[0.020]	[0.018]	[0.016]	[0.018]	[0.016]	[0.015]	[0.014]
Birth year	0.013	0.010	0.000	0.001	0.030	0.021	-0.002	-0.002
	[0.029]	[0.026]	[0.010]	[0.008]	[0.023]	[0.019]	[0.009]	[0.009]
First year	-0.051	-0.031	-0.013	-0.003	-0.007	-0.011	0.030*	0.016**
	[0.035]	[0.027]	[0.014]	[0.011]	[0.029]	[0.025]	[0.015]	[0.007]
Second year	0.017	0.020	-0.013	-0.007	-0.030	-0.012	0.011	0.012
	[0.029]	[0.028]	[0.014]	[0.012]	[0.028]	[0.022]	[0.010]	[0.008]
Third year	0.070**	0.048**	0.028**	0.020*	-0.017	-0.024	-0.002	-0.002
	[0.024]	[0.018]	[0.010]	[0.010]	[0.021]	[0.018]	[0.014]	[0.011]
Constant	0.196***	0.219***	0.195***	0.214***	0.283***	0.215***	0.271***	0.209***
	[0.027]	[0.022]	[0.037]	[0.029]	[0.034]	[0.033]	[0.032]	[0.032]
Observations	6,084	6,084	6,084	6,084	6,084	6,084	6,084	6,084
R-squared	0.145	0.116	0.145	0.116	0.149	0.117	0.149	0.117
Log likelihood	-3338	-2148	-3339	-2148	-3567	-2232	-3564	-2231

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level. All regressions estimated for state-month combinations and include rainy season fixed effects, birth year fixed effects, state fixed effects, and state-specific linear trends. Robust standard errors are clustered at the state level and reported in parentheses.

Appendix Table A2 - Effect of Early-Life Rainfall on Probability of Migrating from Municipality of Birth

	All Individuals	Women Only	Men Only
	(1)	(2)	(3)
Rainfall deviation measures (Method 1):			
Before birth	0.092**	0.118*	0.039
	[0.037]	[0.056]	[0.077]
First year	-0.001	0.055	-0.040
	[0.019]	[0.052]	[0.044]
Second year	0.002	-0.023	0.066
	[0.023]	[0.043]	[0.053]
Third year	0.010	0.021	-0.025
	[0.028]	[0.071]	[0.037]
Constant	-0.015	0.560***	0.144
	[0.047]	[0.099]	[0.118]
Observations	3,981	2,053	1,928
R-squared	0.598	0.642	0.640
Log likelihood	-993.3	-361.8	-397.6
Rainfall deviation measures (Method 2):			
Before birth	0.073**	0.046	0.048
	[0.028]	[0.046]	[0.072]
Birth year	-0.002	0.072	-0.041
	[0.031]	[0.061]	[0.046]
First year	-0.000	-0.034	0.020
	[0.032]	[0.051]	[0.069]
Second year	0.032	0.047	-0.012
	[0.031]	[0.049]	[0.045]
Third year	0.011	0.033	0.001
	[0.044]	[0.062]	[0.059]
Constant	0.014	0.691***	0.003
	[0.042]	[0.094]	[0.135]
Observations	4,050	2,091	1,959
R-squared	0.596	0.638	0.641
Log likelihood	-1019	-382.3	-401.3

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level. All regressions include season of birth fixed effects, birth year fixed effects, state fixed effects, and state-specific linear trends. Robust standard errors are clustered at the state level and reported in parentheses.

References

Achyuta Adhvaryu, Anant Nyshadham, Teresa Molina, and Jorge Tamayo. Helping children catch up: Early life shocks and the Progresa experiment. Technical report, National Bureau of Economic Research, 2019.

Arturo Aguilar and Marta Vicarelli. El Nino and Mexican children: Medium-term effects of early-life weather shocks on cognitive and health outcomes. 2018.

Richard Akresh, Leonardo Lucchetti, and Harsha Thirumurthy. Wars and child health: Evidence from the Eritrean–Ethiopian conflict. *Journal of Development Economics*, 99(2):330–340, 2012.

Richard Akresh, German Caruso, and Harsha Thirumurthy. Detailed geographic information, conflict exposure, and health impacts. 2016.

Harold Alderman, John Hoddinott, and Bill Kinsey. Long term consequences of early childhood malnutrition. *Oxford Economic Papers*, 58(3):450–474, 2006.

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

Douglas Almond and Janet Currie. Killing me softly: The fetal origins hypothesis. *The Journal of Economic Perspectives*, 25(3):153–172, 2011.

Douglas Almond and Bhashkar A Mazumder. Health capital and the prenatal environment: the effect of Ramadan observance during pregnancy. *American Economic Journal: Applied Economics*, 3(4):56–85, 2011.

Mabel Andalón, João Pedro Azevedo, Carlos Rodríguez-Castelán, Viviane Sanfelice, and Daniel Valderrama-González. Weather shocks and health at birth in Colombia. *World Development*, 82:69–82, 2016.

Javier E Baez, Leonardo Lucchetti, Maria E Genoni, and Mateo Salazar. Gone with the storm: Rainfall shocks and household wellbeing in Guatemala. *The Journal of Development Studies*, pages 1–19, 2017.

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

Alan I Barreca. The long-term economic impact of in utero and postnatal exposure to malaria. *Journal of Human Resources*, 45(4):865–892, 2010.

Martina Björkman-Nyqvist. Income shocks and gender gaps in education: Evidence from Uganda. *Journal of Development Economics*, 105:237–253, 2013.

Hoyt Bleakley. Disease and development: evidence from hookworm eradication in the American South. *The Quarterly Journal of Economics*, 122(1):73, 2007.

Hoyt Bleakley. Malaria eradication in the Americas: A retrospective analysis of childhood exposure. *American Economic Journal: Applied Economics*, 2(2):1–45, 2010.

Gustavo J Bobonis. Is the allocation of resources within the household efficient? new evidence from a randomized experiment. *Journal of Political Economy*, 117(3):453–503, 2009.

Carlos Bozzoli, Angus Deaton, and Climent Quintana-Domeque. Adult height and childhood disease. *Demography*, 46(4):647–669, 2009.

Tom Bundervoet and Sonja Fransen. The educational impact of shocks in utero: Evidence from Rwanda. *Economics & Human Biology*, 29:88–101, 2018.

Katy Cornwell and Brett Inder. Child health and rainfall in early life. *The Journal of Development Studies*, 51(7): 865–880, 2015.

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

David Cutler, Winnie Fung, Michael Kremer, Monica Singhal, and Tom Vogl. Early-life malaria exposure and adult outcomes: Evidence from malaria eradication in India. *American Economic Journal: Applied Economics*, 2(2): 72–94, 2010.

Euclides Da Cunha. *Rebellion in the Backlands*. University of Chicago Press, 2010.

Olivier Deschênes, Michael Greenstone, and Jonathan Guryan. Climate change and birth weight. *American Economic Review*, 99(2):211–17, 2009.

John Dobbing. Vulnerable periods in brain growth and somatic growth. *The Biology of Human Fetal Growth*, pages 137–47, 1976.

Erica Field, Omar Robles, and Maximo Torero. Iodine deficiency and schooling attainment in Tanzania. *American Economic Journal: Applied Economics*, 1(4):140–169, 2009.

Andrew D Foster and Mark R Rosenzweig. Microeconomics of technology adoption. *Annual Review of Economics*, 2(1):395–424, 2010.

Luis Miguel Galindo. La economía del cambio climático en México. *Síntesis*, 21, 2009.

Paul Glewwe and Elizabeth M King. The impact of early childhood nutritional status on cognitive development: Does the timing of malnutrition matter? *The World Bank Economic Review*, 15(1):81–113, 2001.

John Hoddinott and Bill Kinsey. Child growth in the time of drought. *Oxford Bulletin of Economics and Statistics*, 63(4):409–436, 2001.

Hilary Hoyne, Diane Whitmore Schanzenbach, and Douglas Almond. Long-run impacts of childhood access to the safety net. *The American Economic Review*, 106(4):903–934, 2016.

Robert Jensen. Agricultural volatility and investments in children. *The American Economic Review*, 90(2):399–404, 2000.

Erik Jonasson and Steven M Helfand. How important are locational characteristics for rural non-agricultural employment? lessons from Brazil. *World Development*, 38(5):727–741, 2010.

Angela Kageyama and Rodolfo Hoffmann. Determinantes da renda e condições de vida das famílias agrícolas no Brasil. *Economia*, 1(2):147–183, 2000.

Seyed M Karimi and Anirban Basu. The effect of prenatal exposure to Ramadan on children's height. *Economics & Human Biology*, 30:69–83, 2018.

Masayuki Kudamatsu, Torsten Persson, and David Strömberg. Weather and infant mortality in Africa. 2016.

Santosh Kumar, Ramona Molitor, and Sebastian Vollmer. Drought and early child health in rural India. *Population and Development Review*, pages 53–68, 2016.

Maarten Lindeboom, France Portrait, and Gerard J Van den Berg. Long-run effects on longevity of a nutritional shock early in life: the Dutch potato famine of 1846–1847. *Journal of Health Economics*, 29(5):617–629, 2010.

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

Jose A Marengo, Roger Rodrigues Torres, and Lincoln Muniz Alves. Drought in Northeast Brazil - past, present, and future. *Theoretical and Applied Climatology*, 129(3-4):1189–1200, 2017.

Gabriel Medina, Camila Almeida, Evandro Novaes, Javier Godar, and Benno Pokorny. Development conditions for family farming: Lessons from Brazil. *World Development*, 74:386–396, 2015.

Edward Miguel. Poverty and witch killing. *The Review of Economic Studies*, 72(4):1153–1172, 2005.

Carlos A Monteiro, Wolney L Conde, and Barry M Popkin. Independent effects of income and education on the risk of obesity in the Brazilian adult population. *The Journal of Nutrition*, 131(3):881S–886S, 2001.

Valerie A Mueller and Daniel E Osgood. Long-term consequences of short-term precipitation shocks: evidence from Brazilian migrant households. *Agricultural Economics*, 40(5):573–586, 2009.

Richard E Nelson. Testing the fetal origins hypothesis in a developing country: evidence from the 1918 influenza pandemic. *Health economics*, 19(10):1181–1192, 2010.

Vikram Pathania. The long run impact of drought at birth on height of women in rural India. *Work. Pap., UC Berkeley*, 2009.

FRM Portrait, TF van Wingerden, and DJH Deeg. Early life undernutrition and adult height: The Dutch famine of 1944–45. *Economics & Human Biology*, 27:339–348, 2017.

V Brahmananda Rao and K Hada. Characteristics of rainfall over Brazil: Annual variations and connections with the southern oscillation. *Theoretical and Applied Climatology*, 42(2):81–91, 1990.

V Brahmananda Rao, Sergio H Franchito, Clovis ME Santo, and Manoel A Gan. An update on the rainfall characteristics of Brazil: seasonal variations and trends in 1979–2011. *International Journal of Climatology*, 36 (1):291–302, 2016.

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

Maria Rosales-Rueda. The impact of early life shocks on human capital formation: Evidence from El Niño floods in Ecuador. *Journal of Health Economics*, 62:13–44, 2018.

Elaina Rose. Consumption smoothing and excess female mortality in rural India. *Review of Economics and Statistics*, 81(1):41–49, 1999.

Manisha Shah and Bryce Millett Steinberg. Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy*, 125(2):527–561, 2017.

Emmanuel Skoufias. Poverty alleviation and consumption insurance: Evidence from PROGRESA in Mexico. *The Journal of Socio-Economics*, 36(4):630–649, 2007.

Emmanuel Skoufias and Katja Vinha. Climate variability and child height in rural Mexico. *Economics & Human Biology*, 10(1):54–73, 2012.

Emmanuel Skoufias and Katja Vinha. The impacts of climate variability on household welfare in rural Mexico. *Population and Environment*, 34(3):370–399, 2013.

Thuan Q Thai and Evangelos M Falaris. Child schooling, child health, and rainfall shocks: Evidence from rural Vietnam. *Journal of Development Studies*, 50(7):1025–1037, 2014.

Gerard J Van den Berg, Maarten Lindeboom, and France Portrait. Economic conditions early in life and individual mortality. *American Economic Review*, 96(1):290–302, 2006.

WHO. Drought: Natural disaster profiles. *World Health Organization, Geneva*, 2012.

Cort J Willmott and Kenji Matsuura. Terrestrial air temperature and precipitation: Monthly and annual time series (1950 - 2014). 2015.