Children of Drought: Rainfall Shocks and Early Child Health in Rural India

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Abstract

Barker's fetal origins hypothesis suggests a strong relationship between in utero conditions, health, and overall child development after birth. Using a nationally representative population survey, this paper analyzes the impact of rainfall on early child health in rural India. We find that drought experienced in utero has detrimental effects on the nutritional status of children. Effects appear to be stronger for boys, low caste children, and children exposed to drought in the first trimester of the mother's pregnancy. Results are robust to alternative definitions of drought. Our estimates speculate that policies aimed at reducing vulnerability to negative rainfall shock may result into improved health and higher human capital accumulation in rain-dependent agrarian countries.

Key Words: Fetal origins hypothesis, undernutrition, rainfall, India

JEL classification: I15; I18; O12; O15

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1 Introduction

Identifying the long-run effects of in utero and early-life conditions has become an important research topic in economics. Since the seminal work by Almond (2006), a growing literature finds that in utero exposure to adverse environments may negatively affect the health and educational attainment later in life (Almond et al., 2009; Banerjee et al., 2010; Lin and Liu, 2014; Maccini and Yang, 2009; Neelsen and Stratmann, 2011). These studies clearly demonstrated that early childhood conditions including the in utero period have a long lasting impact on life expectancy, adult earnings, adult health, and cognition development.

The hypothesis that the in utero period is the most critical period in a person's life was first posited by David J. Barker, a British physician and epidemiologist, who argued that nutritional deprivation of pregnant women impacts the fetus and leads to impaired fetal development with long lasting consequences that continue to persist after birth and even through adulthood (Barker, 1990, 1995).[1] Nowadays the Barker hypothesis is used as a general term to describe how in utero shocks relate to later life outcomes. Therefore, given the strong relationship between in utero conditions and adult outcomes, the fetal origins hypothesis can provide important insights into the understanding of low levels of human capital accumulation in resource-poor countries.

Despite the importance of the in utero condition in predicting health and income of the individuals in later life, the causal impact of the in utero condition on later-life outcomes has remained elusive mainly due to data limitations (Rasmussen, 2001). The challenge lies in finding a truly exogenous variation in the in utero and early life conditions. Nonetheless, in recent years economists have taken advantage of natural experiments that are quasi-random in nature to identify exogenous variation in early environmental conditions. Events such

[1] This hypothesis is commonly known as "fetal origins hypothesis" or as "Barker hypothesis".

as pandemic (Almond, 2006; Banerjee et al., 2010), famine (Neelsen and Stratmann, 2011), armed conflict (Akresh et al., 2012; Lee, 2014), exposure to radioactive emission (Almond et al., 2009), ramadan fasting (Almond and Majumder, 2012), government intervention such as iodine supplementation, hookworm and malaria eradication programs (Bleakley, 2009; Field et al., 2009), and extreme weather shocks (Maccini and Yang, 2009; Shah and Steinberg, 2013) have been frequently exploited to estimate the causal relationship between in utero condition and later life outcomes.

This paper exploits the plausibly exogenous variation in rainfall to examine the effect of in utero exposure to a rainfall shock on health outcomes of children in India. We study the medium-term effect of drought in the year before birth (in utero) and in the year of birth on the health outcomes of children younger than 60 months living in rural India. About 70% of the Indian working population rely on agriculture directly or indirectly for their sustenance and their income is highly volatile due to erratic monsoon rainfall since agriculture is predominantly rain-fed in India. Droughts are common phenomena in India. Given the dependency of rural lives on rainfall, a negative rainfall shock in a year is likely to affect the household income due to reduction in agricultural production as well as food availability which in turn may affect the maternal and fetal nutrition. For developing countries, there is enough evidence to confirm that family income does affect the nutritional status of children (Duflo, 2003; Jensen, 2000).

A number of recent studies have examined the long-term effects of rainfall on health and schooling of children. In an influential paper, Maccini and Yang (2009) noted that higher rainfall in the *year of birth* leads to improved health, schooling, and socioeconomic status for Indonesian women but not for men and discount the importance of in utero exposure to higher rainfall. Similarly, Shah and Steinberg (2013) assess the effect of rainfall variability in India on human capital accumulation and find that children who were exposed to droughts in utero or between birth and age four score significantly worse on literacy and numeracy skills, are more likely to repeat a grade, and are less likely to ever enroll in school. Conversely, there are positive effects on children for higher early-life rainfall. In a study conducted in northeastern Brazil Rocha and Soares (2012) reported that exposure to drought in utero is correlated with higher infant mortality, lower birth weight, and a shorter gestation period. They pointed toward the lack of safe drinking water and a higher incidence of infectious diseases as potential mechanisms rather than the fall in agricultural production and lower nutrient intake.

Even though neither Maccini and Yang (2009), nor Shah and Steinberg (2013) directly measure the channels through which weather affects children's health and cognitive development, they argue for the causal chain operating through the impact that weather variability has on agricultural production and thus, income and nutrition for the rural population. This paper complements this literature by studying child health outcomes of children exposed to in utero rainfall shocks.

We add to this literature by exploiting exogenous variation in monsoon rainfall in India. We use monthly rainfall data at the district level to identify ex-post periods of droughts. Droughts cause harvest failure and put families under severe financial stress when they mainly rely on agriculture as a source of income under severe financial stress. In principle, there is insurance available to protect against this type of risk, but the uptake of such insurance is quite low in our context. In the absence of risk-sharing and consumption smoothing, harvest failure is a severe shock to household income and consequently to health and nutritional status of family members.

We study the reduced-form effect of exposure to droughts during the in utero phase on health outcomes of 0-60 months old children. While Maccini and Yang (2009) and Shah and Steinberg (2013) focus on education of children older than 6 years and adults, respectively, we are, hence, focusing on an important channel through which these previous findings can be explained. We show that exposure to droughts in utero is associated with lower weight-for-age z-scores and increased probabilities of being underweight. However, in utero exposure to drought does not seem to affect the anemic status of children. Our results also indicate that drought in the year of birth is also an important predictor of health, a finding similar to Maccini and Yang (2009).[2] We also find evidence of heterogeneity in the effects of drought on a child's health.

The rest of the paper is organized as follows: In section 2 we lay out the conceptual framework. Section 3 presents our econometric specification and section 4 describes the anthropometric and rainfall data. In section 5 we present the main regression results and robustness. Section 6 discusses the potential threats to our identification strategy before we conclude in section 7.

2 Conceptual Framework

The underlying economic framework in this study is adopted from Maccini and Yang (2009) which is an extension of the health production model developed by Grossman (1972). Grossman (1972) defines health as a capital stock that varies over time and that produces an output of healthy time. Variation in the health stock is justified by investments in health that increase the capital stock and by depreciation of the stock as the individual ages. Grossman's model assumes that the health stock at time t, H_t, is a function of an initial health endowment H_0, vector of health inputs N_1,...,N_t, time-invariant demographic characteristics X (gender, age, birth order, caste, parent's education, economic status), availability and access to village infrastructures V_0,...,V_t, and the disease environments faced by the individuals in the community D_0,...,D_t. The health production model can be described as follows:

$$H_t = h(H_0; N_1, ..., N_t; X; V_0, ..., V_t; D_0, ..., D_t) \tag{1}$$

Barker's fetal origins hypothesis argued that health conditions in adult life are affected by changes in the intrauterine environment. Thus, eq(1) can be modified to include this

[2] Maccini and Yang (2009) examined the effect of higher rainfall in the year of birth, whereas we look at the effect of lower rainfall.

relationship between in utero conditions and childhood health as below:

$$H_t = h(H_{-1}; H_0; N_1, ..., N_t; X; V_0, ..., V_t; D_0, ..., D_t) \tag{2}$$

where H_{-1} captures the in utero conditions.

In addition to directly affecting H_t as in eq(2), the in utero conditions may also affect H_t indirectly by influencing the initial health endowment H_0. Adverse in utero conditions may affect the birth weight of children or other health conditions at birth. Furthermore, genetic components G also play an important role in determining H_0; however, the environmental circumstances R_0 , village infrastructures, and disease environments may also have a long-lasting impacts on H_t (Maccini and Yang, 2009). The initial health endowment H_0 will depend on the following factors:

$$H_0 = k(H_{-1}(R_{-1}); G; R_0; V_0; D_0) \tag{3}$$

Based on the conceptual framework outlined in eq(1)-(3), we argue that rainfall shocks in early life can affect health status in period t via H_{-1} and H_0. We can think of two mechanisms through which rainfall shock may impact health outcomes of the child. The first channel is through income and food price effects. In a country like India where agriculture is mostly rain-fed and the majority of rural households rely on agriculture for their income, the most immediate impact of erratic and deficient rainfall on rural livelihoods is on crop failure and on agricultural income derived from crop sales (Burgess et al., 2013; Rao et al., 1988; Shah and Steinberg, 2013). Due to crop failure, household income declines steeply which in turn affects the maternal and fetal nutrition through reduced consumption levels.[3] Consumption is also affected due to rising food prices because there is a shortage of food due to harvest failure. Auffhammer et al. (2012) demonstrates that drought and extreme rainfall negatively affected rice yield (harvest per hectare) in predominantly rainfed areas during 1966-2002 in

[3]Reduced income may also affect expenditure incurred on health goods such as expenditures on seeking medical care when sick.

India, with drought having a much greater impact than extreme rainfall. A Government of India document reports that drought in year 2009 was one of the most severe in decades, with rice harvest declining by 14% (Commission for Agricultural Costs and Prices, 2010).

Aside from the income channel, child nutrition and health may also be affected by the disease environment *(D)* in the community. However, the evidence of drought on disease environment is ambiguous. On the one hand, drought may affect availability and quality of drinking water and there is some evidence from Sub-Saharan Africa indicating that water scarcity during dry seasons is associated with a higher prevalence of diarrhea and infectious diseases due to increased consumption of unsafe water and reduced hygiene practices (Bandyopadhyay et al., 2012; Rocha and Soares, 2012). On the other hand, drought may have positive disease impact from reduction in water-borne diseases.[4] Furthermore, disease environments may worsen due to drought induced higher infant mortality in India (Burgess et al., 2013; Rose, 1999), in Brazil (Rocha and Soares, 2012), and in Africa (Kudamatsu et al., 2014).[5] The combined impact of negative income effect and negative disease effect due to drought on child health is unambiguous; however the impact resulting from the interaction of negative income effect and positive disease effect will have on health outcomes is not straightforward. But there is some evidence suggesting that income effects on health dominate the disease effect during drought conditions (Jacoby et al., 2013).

3 Econometric Specification

We use cross-sectional child level data to analyze the effect of in-utero exposure to drought on early child health. We use the standardized z-score for weight-for-age and anemia as measures of early child health. The key independent variable is "exposure to drought" in the year before birth. The most challenging aspect of this study is to merge the rainfall data

[4]Deficient rainfall in developing countries is typically linked to lower incidence of water- and vector-borne diseases (Confalonieri et al., 2007, Rabassa et al., 2012).

[5]It is also possible that infant mortality may be lower due to drought because of decreased opportunity cost of labor during drought periods, resulting in more breastfeeding.

with the child-level observations; this would require accurate information on the latitude and the longitude of the district. However, we are able to map these two dataset because the DLHS data allows us to identify the exact dates of birth and the current district of residence. We merge these birth information with the rainfall data to identify the cohort exposed to drought.We assume that the occurrence of a drought or rainfall shock is a quasi-random event across and within districts, therefore, the assignment of exposure to a drought in-utero is also of a quasi-random nature. We give a detailed definition of drought in the next section. The important part for our identifying assumption is that the drought definition is solely based on year-to-year variation *within* a district, which is plausibly exogenous.

We model the effect of in utero rainfall shock on early child health using the following linear model:

$$Y_{ijy} = \alpha + \beta_1 D_{j,t-1} + \beta_2 D_{j,t} + \delta X'_{ij} + \gamma_j + +\theta_y + \epsilon_{ijy} \tag{4}$$

where Y_{ijy} is the health outcome for individual i, born in district j, and in quarter y. $D_{j,t-1}$ and $D_{j,t}$is an indicator equal to 1 if there was a drought in the district of birth in the year before birth and the year of birth, respectively. The vector X' includes controls for parent's education (whether mother and/or father are literate), religion (an indicator of whether the household is Hindu), birth order of the child, child's age in months, gender of the child, an indicator of whether the household belongs to a socially disadvantaged schedule caste (SC) or schedule tribe (ST) communities, standard of living index, and year of interview. γ_j are district fixed-effects that are intended to control any district specific time invariant characteristics. θ_y is the vector of quarter of birth that captures the seasonality patterns in fetal health.

ϵ_{ijy} is an idiosyncratic error term. Since exposure is invariant within districts and there is a possible correlation of errors within districts, standard errors are clustered at the district level as suggested by Moulton (1990) and Pepper (2002).[6]

[6]While clustering standard errors at some geographical level is common in the literature (see Maccini and Yang, 2009; Shah and Steinberg, 2013; Yamauchi, 2012), it is important to note that there might also

β_1 is the main coefficient of interest and quantifies the impact of the rainfall shock in utero on health outcomes of the children. Maccini and Yang (2009) find evidence that rainfall in the year of birth is highly relevant in determining health and education in adult life. Similar results are obtained from Shah and Steinberg (2013). Therefore, our main specification also includes drought in the year of birth and its impact is given by β_2.

As long as the rainfall shock is exogenous, that is $\mathrm{E}(D, \epsilon_{ijy}) = 0$, the coefficient estimate of β_1 is unbiased and provides the causal impact of rainfall shock on early child health. However, there are several potential channels at work that may affect child health at birth, for example, selective migration, selective mortality, and selective fertility. These selection biases may nullify our identifying assumption. We, therefore, analyze and discuss these threats to our identification in section 6 and argue that our main results are not confounded by these biases.

To capture heterogeneity in the effects of drought on health outcomes, we estimate eq(4) by gender of the child, household caste, mother's education, household's economic status, and quarter of birth.

4 Data

4.1 Rainfall Data

Monthly rainfall data for the years 1970 to 2005 are available from the *National Meteorological Service of Germany.* The data extends to 591 districts from 29 states and 7 union territories out of 593 identified districts in the 2001 census. The district rainfall amount is

be correlation between two very close locations that are situated in different geographical locations, i.e. two villages where one is situated at the border of district A and the other at the border of district B. Aguilar (2011) corrects for spatial correlation and finds that standard errors increase when allowing for spatial correlation. Anthropometric estimations are most sensitive to the correction but the overall significance of the results do not change. Unfortunately the data used here do not allow for such a correction. For this, detailed information of the location of the households, i.e. longitude and latitude data would be needed.

recorded monthly where precipitation refers to the amount of rain in milliliter per acre. [7]

We use the Indian Meteorological Department (2010) definition of drought to identify the year of drought. The Indian Meteorological Department (2010) defines a drought year as a year in which monsoon rainfall, the rain between June and September, falls below 75% of its long-term average value, i.e. when the monsoon rainfall deficit exceeds 25%. The long-term average is calculated using the monthly rainfall data from 1970 to 2000 for each district.[8] Based on this definition, we define a year as a "drought year" if the monsoon rainfall is less than 75% of the district's long-term average rainfall. In equation (4), the drought year (D) is a dummy equal to one if rainfall is less than 75%, and 0 otherwise.

Figure A.1 plots the occurrence of droughts as percent of the total number of districts. The focus lies on the years 1995–2005 which is the period that we will link with the health data. Between 0 to 7 droughts within districts occurred in the observed 21 years period. As illustrated in Figure A.1, the distribution is skewed to the right with a median of 2 droughts per district. In less 25% of all districts, no drought between 1995 and 2005 was identified, while in less than 1% of all districts, the figure increases to 6 or more droughts.

There is a high variation in the number of districts that show drought conditions over time as shown in Figure A.2. The years 1999 and 2002 were highly rainfall deficient with more than 124 districts classified with drought. This corresponds to the 75% percentile of the distribution. Lower drought exposure is measured for 1996 and 1998 were only 38 districts were classified with a drought, i.e. falling below the 25th percentile.

In addition to the IMD definition of drought, we also use two alternative definitions of drought: (1) monsoon rainfall below the 20th percentile of the district's historical monsoon rainfall (Shah and Steinberg, 2013) and (2) monsoon rainfall that deviates at least one standard deviation from the district's historical monsoon rainfall (Parthasarathy et al., 1994).

[7] There are missing rainfall data for Nicobar and Lakshadweep which are two Indian union territories in the Indian Ocean and not connected to the mainland.

[8] The Indian Meteorological Department (2010) makes a further distinction between moderate (monsoon rainfall deficit between 26% and 50%) and severe droughts (monsoon rainfall deficit exceeding 50%). The definition adopted here encompasses moderate and severe droughts.

As depicted in Figure A.3, the number of droughts per year evolve very similarly using the two alternative measures of drought assessment. The definition using the 20th percentile and our main definition constitute the upper and lower bound, respectively.

4.2 Health Data

Information on child health are drawn from the second wave of the District Level Household Survey (DLHS-2). The DLHS is a survey of representative households covering all districts of India containing approximately 99% of India's population. The survey is similar to other demographic and health surveys (DHS) conducted in several other countries including India. The DLHS is analogous to the National Family Health Survey (NFHS) in terms of survey structure and the instrument, however, the main advantage of DLHS over NFHS is the sample size. The DLHS sample is approximately five times lager than the NFHS sample, therefore we prefer the DLHS over the NFHS to carry out our analysis.

The DLHS-2 interviewed 507,000 currently married women between 15 and 44 years and 300,000 husbands in all 593 Indian districts between 2002 and 2004. Information is available in two separate data sets: the women's survey provides information on the household's structure and background; information on women's fertility history, usage of health clinics; and health awareness and vaccination history of 0-5 years old children. Additionally, the children sample contains measured weight and hemoglobin level of children under-five years (International Institute for Population Sciences, 2006). For our analysis, the women and the children data sets are merged, and finally the merged data set is linked with the rainfall data to identify cohort exposed to an in utero drought.

The final analytical sample is restricted to only rural households, since adverse rainfall events should mainly have an effect on the rural and on agriculture dependent population. According to the 2001 Census, urban areas are defined as areas with a population of more than 5,000 persons or areas where most male employment is not allocated to agriculture (Desai et al., 2009). By imposing this sample restriction, it is assumed that there is none or only little migration, i.e. that the district of residence coincides with the district of birth. Since we focus on very young children, this assumption cannot be very restrictive. Additionally, we show later that rural migration is, in fact, very little.[9] Several other studies have also shown that cross district migration in rural India is very limited (Topalova, 2010). The summary statistics for the main variables used in the study are reported in Table 1.

We center our analysis on weight-for-age z-scores (WAZ) and anemia among children under age 5. Weight is an important marker for nutritional status of children and it captures the deficiency in physical growth of the child. The prevalence of underweight among children in India is highest in the world, and nearly double that of Sub-Saharan-Africa. The Hunger and Malnutrition (HUNGaMA, 2011) report by the Naandi Foundation (2011), a study based on a survey of height and weight of children across six states, found that as many as 42 percent of children under the age of five are severely or moderately underweight. The study also shows a higher prevalence of underweight in rural areas than in urban areas; higher among scheduled castes and scheduled tribes than among other castes; and, higher in the lowest wealth quintile than in high wealth quintile.

The incidence of anemia is also very high in India. The third National Family Health Survey (NFHS) 2005 to 2006 revealed that at least 80% of Indian children aged 12 to 23 months were anemic. Anemia was more prevalent among rural children, and the majority of India's population (72.2%) is rural. Combating childhood iron-deficiency anemia is a public-health priority, because anemia is associated with impaired cognitive and psychomotor development. Therefore, we analyze the effect of in utero exposure to drought on WAZ and anemia, an important marker of childhood nutritional status.

[9] Any attenuation bias due to measurement error will cause our estimates to be biased towards zero. Our estimates would then constitute a lower bound of the true effect.

4.3 Outcome Variables

Weight was measured for children under 5 years as part of the DLHS-2. The weight-for-age z-score (WAZ) are calculated for these children using the World Health Organization's (WHO) 2006 growth standards (de Onis et al., 2006). While absolute weight indicates child growth relative to the sample mean, the z-scores provide information on how the anthropometric characteristic of a child compares to a reference population. Weight-for-age is used to measure malnutrition among young children. In addition to the WAZ score, we also define *underweight* equal to 1 if WAZ $<$ -2, and 0 otherwise; and *severely underweight* equal to 1 if WAZ $<$ -3, and 0 otherwise. Furthermore, we also include anemic status of the children as an outcome variable. *Anemia* is defined as measured hemoglobin level below 8g/dl.[10]

4.4 Descriptive Statistics

Table 1 presents the summary statistics of the variables used in the analyses. The average weight is close to 11 kg. The mean WAZ z-score is around 1.85 with 46 percent of the children having a z-score below -2 standard deviations. and 22 percent of the children having a z-score below -3 standard deviations, meaning that approximately two-third of the children in India are suffering from some degree of malnourishment during the data period.

The average hemoglobin level in the sampled children is about 9.5 g/dl. In the sample, about 46% of the children suffer from at least moderate anemia. The average age of children is 31 months and about 48% are girls. 38% of children belong to low caste households (scheduled caste and scheduled tribe) and majority of the children (64%) are poor. Households belonging to lowest wealth index are defined as poor (for estimation of wealth index, see IIPS (2006)). Mother's literacy rate is less than 50% while father's literacy rate is slightly higher than the mother's literacy rate (67%). The distribution of birth across quarters does not differ much-it ranges from 23% in first quarter to 27% in fourth quarter. The majority of the children are

[10] Mild, moderate and severe anemia are defined as having a hemoglobin level of below 11 g/dl, 8 g/dl and 5g/dl, respectively (Ladu Singh et al., 2006).

Hindu (98%). By excluding observations with missing information on any of these variables reported in Table 1, we get a final sample of 156,869 children from 533 districts of India.[11]

TABLE 1

Characteristics of the sample of rural children aged 0 months to 60 months.

Variable	Mean	S.D.
Weight-for-Age (WAZ)	-1.85	1.54
Undernutrition (WAZ < -2)	0.46	
Severe Undernutrition (WAZ < -3)	0.22	
Anemia	0.46	
Child gender (Girl)	0.48	
Child age (months)	30.91	17.74
Low caste (SC & ST)	0.38	
Mother is literate	0.40	
Father is literate	0.67	
Hindu religion	0.82	
Poor	0.64	
Birth order	2.87	1.89
Born in Quarter 1 (Q1)	0.23	
Born in Quarter 2 (Q2)	0.27	
Born in Quarter 3 (Q3)	0.27	
Born in Quarter 4 (Q4)	0.23	
Observations	156,869	
Number of districts	533	

Notes: Authors calculations from the DLHS-2. Included in the sample are all rural children between 0 and 60 months and with non-missing information on all covariates. Weight is measured in kg. Anemia is defined as measured hemoglobin level below 8 g/dl. Schedule caste (SC) and Schedule tribe (ST) are socially disadvantaged caste. Poor is defined as the household in the lowest wealth index category. For binary variables, mean indicates the percentage of the sample with the particular characteristic.

5 Results

5.1 Main effects

Table 2 presents the results from our main specification in eq (4). It summarizes the causal relationship between in utero drought exposure and undernutrition and anemia among

[11] About one third of the observations are excluded due to the restriction on children from rural areas.

children under-five. To keep the presentation simple, coefficients of only "drought in the year before birth" and "drought in the year of birth" are reported, however, the full results for the specification are available on request. Col (1), (3), (5), and (7) report the estimated coefficient without district fixed-effects, while col (2), (4), (6), and (8) additionally includes district fixed-effects. The district fixed effects control for the impact of the district-based policies on health outcomes as well as any general agro-climatic or economic conditions that vary across districts. Inclusion of district fixed-effects would remove any biases due to systematic differences across districts. This also implies that we are exploiting exogenous variation in rainfall for each district over years. Column (1) presents the result of a general multiple linear regression model while columns (2) to (8) are based on a linear probability model. Our preferred specification is the model with the district fixed-effects.

Results indicate that drought exposure in the year before birth (in utero) or year of birth has a negative and statistically significant effect on weight-for-age scores. In utero exposure to drought (D_{t-1}) reduces the weight-for-age z-score by 0.12 (column (1)). Drought in the year of birth (D_t) also has a significantly negative impact on weight-for-age z-scores. Accounting for district heterogeneity, the coefficient of D_{t-1} becomes slightly smaller but stays highly significant and implies that children exposed to drought in the year before birth experience, ceteris paribus, a reduction on weight for age by 0.10 s.d.. The D_t coefficient is slightly smaller than D_{t-1}, i.e. exposure to drought in the year of birth reduces the weight-for-age score by 0.08 s.d.. The statistically significant coefficient estimates of 0.10 and 0.08 points are non-trivial given that a z-score of -2 is indicative of underweight or malnourishment and the average weight-for-age z-score for the children in the sample is -1.85.

The reduction of the weight-for-age z-score translates into increased probabilities of being underweight (z-score<-2) or severely underweight (z-score<-3). The average probability of being underweight increases by 2 percentage points if there was a drought in the year before birth (col 4). The results for severe underweight are quantitatively similar to those of underweight. Children exposed to drought in utero are 2.1 percentage points more likely to be severely underweight. This is quite remarkable since the incidence of severe underweight is much lower and thus the same absolute percentage point reduction is a much stronger relative effect. In-utero exposure to drought is not statistically significantly correlated with anemia. The sign is positive indicating harmful effects of drought on hemoglobin level but the standard errors are imprecisely estimated, thereby wiping out the statistical significance of the coefficient.

TABLE 2

Effect of Exposure to Drought on Child's Health, Age 0–5 years

	WAZ		WAZ<-2		WAZ<-3		Anemia	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought t-1	-0.115***	-0.100***	0.024***	0.017**	0.031***	0.021***	0.005	0.001
	(0.037)	(0.033)	(0.009)	(0.008)	(0.008)	(0.008)	(0.011)	(0.005)
Drought t=0	-0.133***	-0.077***	0.032***	0.015**	0.028***	0.011*	0.017	0.004
	(0.030)	(0.024)	(0.008)	(0.007)	(0.007)	(0.006)	(0.011)	(0.005)
Child's age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District f.e.	No	Yes	No	Yes	No	Yes	No	Yes
Mean	-1.85	-1.85	0.46	0.46	0.22	0.22	0.46	0.46
Observations	155,937	155,937	155,937	155,937	155,937	155,937	158,547	158,547

Notes: Robust standard errors, clustered at district level, are in parentheses. Col 1-2 report OLS coefficient from a general multiple linear regression model while Col 3-8 report OLS coefficient from a linear probability model. **Controls**: Gender, schedule caste/tribe, father literacy, mother literacy, religion (indicator for hindu), poverty (indicator of low standard of living index), birth order, age in month, year of interview, quarter of birth f.e., district f.e.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Heterogeneous effects

5.2.1 Gender and caste heterogeneity

In India, about 60% of agricultural land is rain-dependent, and thus susceptible to fluctuations in weather. Although we do not test it in our study but we do speculate that the main pathway through which exposure to drought would affect the health of pregnant women and children is through fall in agricultural output. Fluctuations in agricultural production affect consumption and thereby have the potential of adversely affecting food intake by pregnant women. Adverse weather events can also have a detrimental effect through changes in the prevalence of certain types of diseases and ailments associated with extreme weather conditions.

It is quite plausible that coping strategies used during periods of food scarcity may vary depending on the household's socio-economic status. Households belonging to scheduled caste and scheduled tribe are more likely to face resource-constraints to cope up with food shortage. The effect of drought may be modified by the education level of household members. Similarly, the wealth status of a household may also affect the intensity of the effect of drought because rich and wealthy households can use their savings during the period of food scarcity. Therefore, in light of these modifying variables, it is of tremendous policy interest to estimate the heterogeneous effect of drought on early weight-for-age and anemic status of children. The heterogeneous effects of in utero drought exposure are presented in Table 3-6. Tables 3 and 4 report the results by gender and household caste, respectively. In Table 3, we find that boys and girls are both negatively affected by drought.

TABLE 3

Differential Effect of Drought Shock on Child's Health, By Gender of the Child

	WAZ		WAZ<-2		WAZ<-3		Anemia	
	Boy	Girl	Boy	Girl	Boy	Girl	Boy	Girl
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought t-1	-0.109***	-0.086**	0.017*	0.016*	0.022**	0.019**	-0.004	0.007
	(0.036)	(0.034)	(0.009)	(0.009)	(0.008)	(0.008)	(0.006)	(0.007)
Drought t=0	-0.092***	-0.061**	0.017**	0.014*	0.010	0.013*	0.002	0.005
	(0.027)	(0.025)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)
Child's age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District f.e.	Yes	Yes	Yes	Yes	yes	Yes	Yes	Yes
Observations	80,750	75,187	80,750	75,187	80,750	75,187	82,572	75,975

Notes: Robust standard errors, clustered at district level, are in parentheses. Col 1-2 report OLS coefficient from a general multiple linear regression model while Col 3-8 report OLS coefficient from a linear probability model. **Controls**: Schedule caste/tribe, father literacy, mother literacy, religion (indicator for hindu), poverty (indicator of low standard of living index), birth order, age in month, year of interview, quarter of birth f.e., district f.e.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regardless of gender, children exposed to drought in the year before birth are more likely to have lower weight-for-age, will be underweight, and will be severely underweight. However, we do not find any significant impact on probability of being anemic. Drought in the year of birth is also important in explaining the health outcome, but the magnitude of this coefficient is slightly smaller than the coefficient in year t-1. The t-1 coefficient for boys is slightly larger than that for girls supporting the biological/medical literature that boys are more vulnerable in the womb than girls (Barker et al., 2010). The stronger results for boys cannot be due to gender bias because we are considering in utero period in rural areas where access to gender determination facility is rare. Moreover, the Government of India banned fetal sex-determination in 1996, therefore, it is very improbable that many parents are able to know the gender of the child before birth. Hence, it is very plausible that the differential effect of drought by gender is due to biological factors as the medical literature indicates that boys are more fragile than girls in utero. Our results are different from that of (Maccini and Yang, 2009) since they did not find any significant effect for males. However, our results for the sub-sample analysis should be interpreted with some caution, because we are comparing differences in point estimates that are not necessarily statistically significant but yet informative.

In Table 4, we explore the impact of rainfall shock by caste of the household. The effects of drought vary by caste. The effect of drought is larger for low caste children compared to high caste. Once again, no significant effects were found on anemia. Low caste children are 2.6 percentage points more likely to be severely underweight if they were exposed to drought in the year before birth. The magnitude of this effect is sizable because the baseline probability of being severely underweight is 23 percent in the low caste sample. This corresponds to an increase in the probability of being severely underweight by 11.3 percent ($\frac{2.6}{0.23}$).

5.2.2 Wealth and mother's education heterogeneity

In Tables 5 and 6, we analyze the effect of drought exposure by wealth status of the household and education level of the mother. The magnitude of the effect of drought in

TABLE 4

Differential Effect of Drought Shock on Child's Health, By Caste

	WAZ		WAZ<-2		WAZ<-3		Anemia	
	Low caste	High caste	Low caste	High caste	Low caste	High caste	Low caste	High caste
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought t-1	-0.111***	-0.097***	0.020*	0.017*	0.026***	0.017**	-0.003	0.004
	(0.041)	(0.037)	(0.011)	(0.009)	(0.010)	(0.009)	(0.008)	(0.006)
Drought t=0	-0.049	-0.096***	0.013	0.018**	0.008	0.013*	-0.004	0.008
	(0.030)	(0.026)	(0.009)	(0.007)	(0.008)	(0.007)	(0.007)	(0.005)
Child's age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District f.e.	Yes	Yes	Yes	Yes	yes	Yes	Yes	Yes
Observations	59,598	96,339	59,598	96,339	59,598	96,339	58,696	99,851

Notes: Robust standard errors, clustered at district level, are in parentheses. Col 1-2 report OLS coefficient from a general multiple linear regression model while Col 3-8 report OLS coefficient from a linear probability model. **Controls**: Gender, father literacy, mother literacy, religion (indicator for hindu), poverty (indicator of low standard of living index), birth order, age in month, year of interview, quarter of birth f.e., district f.e.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

year t-1 differs across poor and non-poor households. Poor children have a 1.8 percentage points higher probability of being underweight. Surprisingly, the effect is larger for non-poor households for severely underweight outcome. Similar to previous results, exposure to drought has no significant effect on anemia (column 8, Table 5).

Turning to the differential effect by mother's education level in Table 6, we find significant and negative effect of drought on the probability of being underweight for children of mothers with less than primary schooling. Children experience an increased probability of 1.9 percentage points of being underweight if they are born after a drought. Since 50% of the children of less than primary schooled mothers are underweight, this translates to an increase in the probability of being underweight by 3.8%. The results also indicate that exposure to drought in the period t-1 increases the probability of being severely underweight by 8.4% at the mean severe undernutrition of 25% among children born mothers with fewer than five years of schooling. We do not find any evidence of rainfall shock having a significant effect on anemia among the under-five children.

TABLE 5
Differential Effect of Drought Shock on Child's Health, By Wealth Index

	WAZ		WAZ<-2		WAZ<-3		Anemia	
	Poor	Non poor	Poor	Non poor	Poor	Non poor	Poor	Non poor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought t-1	-0.096**	-0.103***	0.018*	0.015*	0.018*	0.023***	-0.004	0.007
	(0.041)	(0.034)	(0.010)	(0.009)	(0.009)	(0.008)	(0.007)	(0.006)
Drought t=0	-0.088***	-0.064**	0.018**	0.012	0.015**	0.006	0.002	0.006
	(0.028)	(0.028)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)
Child's age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District f.e.	Yes	Yes	Yes	Yes	yes	Yes	Yes	Yes
Observations	99,120	56,817	99,120	56,817	99,120	56,817	99,797	58,750

Notes: Robust standard errors, clustered at district level, are in parentheses. Col 1-2 report OLS coefficient from a general multiple linear regression model while Col 3-8 report OLS coefficient from a linear probability model. **Controls**: Gender, schedule caste/tribe, father literacy, mother literacy, religion (indicator for hindu), birth order, age in month, year of interview, quarter of birth f.e., district f.e.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.3 Effect by quarter of birth

Previous research has shown a high degree of correlation between health and season of birth. Lokshin and Radyakin (2012) found that children born during the monsoon months have lower height-for-age compared to children born during the winter months. Tanaka et al. (2007) showed that seasons and months of birth influenced the height and weight of schoolchildren. Therefore, to capture the seasonality patterns in fetal health we include the vectors of quarter of birth in eq (4). A related policy relevant question is to explore which trimester during the fetal growth is the most critical period in influencing health of the children. Yamauchi (2012) argued for rural Indonesia that the children born after the main harvest should have significantly better outcomes. In India, this corresponds to the kharif (monsoon crops) and rabi (winter crops) harvest. However, it is very difficult to accurately map the kharif and rabi season with quarter of birth and then to trimester of birth. Nevertheless, in this section we attempt to explore the differential effect of drought by quarter of birth. This, however, does not identify the trimester of pregnancy that is most sensitive to health shocks implied by adverse weather conditions.

TABLE 6

Differential Effects of Drought on Child's Health, By Mother's Education

	WAZ		WAZ<-2		WAZ<-3		Anemia	
	Below Primary	Primary	Below Primary	Primary	Below Primary	Primary	Below Primary	Primary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought t-1	-0.105***	-0.089**	0.019**	0.014	0.021**	0.020***	-0.005	0.011*
	(0.038)	(0.037)	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)
Drought t=0	-0.088***	-0.059**	0.019**	0.010	0.017**	0.002	0.003	0.006
	(0.027)	(0.029)	(0.008)	(0.009)	(0.007)	(0.007)	(0.006)	(0.007)
Child's age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Birth Quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,959	53,978	101,959	53,978	101,959	53,978	101,959	53,978

Notes: Robust standard errors, clustered at district level, are in parentheses. Col 1-2 report OLS coefficient from a general multiple linear regression model while Col 3-8 report OLS coefficient from a linear probability model. **Controls**: Gender, schedule caste/tribe, father literacy, religion (indicator for hindu), poverty (indicator of low standard of living index), birth order, age in month, year of interview, quarter of birth f.e., district f.e.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The monsoon season in India runs from June to September. The kharif crops depend highly on monsoon rainfall and they are harvested from October to February. Therefore, for the agriculture reliant rural population, the period between October and February can be identified as the critical nutritional period. The cohort born in the first quarter after a drought year would have been exposed to undernutrition in the third trimester of pregnancy, the cohort born in the second quarter in the second and third trimester and the children born in the third quarter would have been exposed to undernutrition in the first trimester of pregnancy. There might still be deleterious effects for the fourth quarter cohorts depending on the actual beginning of the rabi season, that possibly ends the food shortage.[12] Furthermore, the fourth quarter cohorts are affected by droughts in the year before birth when mothers who conceive right after the food shortage have not yet recovered and are physically weak and undernourished from the beginning of pregnancy onwards. Increasing prices that arise from bad harvest seasons further prolong the effect of adverse rainfall shocks.

To test for the relevance of trimester of gestation, we expand eq(4) to include an interac-

[12]Note that a delay of the rabi season could also imply that the first quarter cohort is exposed to the drought even after birth.

tion term of drought in (t-1) and quarter of birth. We continue to control for drought in year of birth. The quarter of birth effects are presented in Table 7. The coefficient estimates of some of the interaction terms of drought and quarter of birth are statistically significant. In column 2, significant impacts of drought appear only in third and fourth quarters suggesting that children born in third and fourth quarters in the year after drought are more likely to be underweight compared to children born in first and second quarters. This implies that exposure to drought in the first trimester (embryonic stage) is the most critical period for child health. Rocha and Soares (2012) finds that the embryonic (first trimester) and fetal stages (second trimester) both are significantly affected by rainfall shock in Brazil. The coefficients of third quarter is about three times larger than coefficients of first quarter but first quarter impacts are imprecisely estimated. For anemia, significant impact of rainfall shock continues to be elusive.

TABLE 7

Differential Effects of Drought on Child's Health, By Quarter of Birth

	WAZ	WAZ <-2	WAZ <-3	Anemia
	(1)	(2)	(3)	(4)
Born Q1, drought t-1	-0.050	0.000	0.010	0.002
	(0.035)	(0.010)	(0.008)	(0.008)
Born Q2, drought t-1	-0.077*	0.010	0.014	0.010
	(0.040)	(0.010)	(0.010)	(0.008)
Born Q3, drought t-1	-0.154***	0.032***	0.031***	0.002
	(0.042)	(0.011)	(0.010)	(0.007)
Born Q4, drought t-1	-0.117**	0.027**	0.028***	-0.011
	(0.053)	(0.011)	(0.011)	(0.007)
Child's age	Yes	Yes	Yes	Yes
Birth quarter f.e.	Yes	Yes	Yes	Yes
District f.e.	Yes	Yes	Yes	Yes
Observations	155,937	155,937	155,937	158,547

Notes: Notes: Robust standard errors, clustered at district level, are in parentheses. Col 1-2 report OLS coefficient from a general multiple linear regression model while Col 3-8 report OLS coefficient from a linear probability model. **Controls**: Gender, schedule caste/tribe, father literacy, mother literacy, religion (indicator for hindu), poverty (indicator of low standard of living index), birth order, age in month, year of interview, quarter of birth f.e., district f.e..
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Robustness

As discussed before, we also used two alternative definitions of drought: (1) monsoon rainfall below the 20th percentile of the district's historical monsoon rainfall (Shah and Steinberg, 2013) and (2) monsoon rainfall deviates at least one standard deviation from the district's historical monsoon rainfall (Parthasarathy et al., 1994). The results are summarized in Table 8. The first four columns show the results from the model using the rainfall below the 20th percentile, while the last four columns show the results from the model using the standard deviation shortfall from the mean. In both specifications, results are qualitatively similar to our main results reported in Table 2. Drought in the year before birth and in the year of birth both have a statistically significant effects on child health. For the weight-for-age z-score, we find qualitatively similar effects with a slightly smaller WAZ as a result to drought exposure, which translates in increased probabilities of being underweight or severely underweight. The magnitude of the coefficients is somewhat smaller than in our main specification. For the second alternative definition, the coefficient for severe undernutrition is not statistically different from zero at any conventional levels. In comparison to the previous results, rainfall shock experienced in utero and in the year of birth affect the probability of being anemic in our first alternative specification ceteris paribus by 0.8 and 1 percentage point, respectively.

In our second robustness check, we include lags of droughts to test whether the coefficient of the in utero drought dummy and of the dummy for drought in the year of birth are not catching up any other effects unrelated to our drought treatment. Hence, including a lag for drought two and three years before birth serves as a placebo kind of test and we expect the coefficient for drought two years and three years before birth to be unrelated to the child's current health status.

The results of this second robustness check are presented in Table 9. The insignificant coefficients of drought two and three years before birth confirm that the placebo is in fact no

TABLE 8
Robustness Check, Alternative Definitions of Droughts

	WAZ	WAZ<-2	WAZ<-3	Anemia	WAZ	WAZ<-2	WAZ<-3	Anemia
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought t-1	-0.064**	0.012*	0.015**	0.008*	-0.056**	0.011	0.012*	0.004
	(0.027)	(0.006)	(0.006)	(0.004)	(0.028)	(0.007)	(0.006)	(0.005)
Drought t=0	-0.057***	0.011*	0.010**	0.010**	-0.054**	0.012*	0.008	0.004
	(0.022)	(0.006)	(0.005)	(0.004)	(0.023)	(0.006)	(0.005)	(0.004)
Child's age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	155,937	155,937	155,937	158,547	155,937	155,937	155,937	158,547

Notes: Coefficients reported. Standard errors in parentheses. **Alternative definition 1)**: Monsoon rainfall below 20th percentile; **Alternative definition 2)**: monsoon rainfall deviates at least one standard deviation from the district's historical monsoon rainfall. **Controls**: Gender, schedule caste/tribe, father literacy, mother literacy, religion (indicator for hindu), poverty (indicator of low standard of living index), birth order, age in month, year of interview, quarter of birth f.e., district f.e..

treatment in the sense of a shock that affects weight-for-age and undernutrition of children aged 0-60 months and supports our identification strategy. Furthermore, the magnitude of the estimated coefficients for D_{t-1} and D_t are very comparable to the results presented in Table 2 and retain their statistical power. The coefficient for drought two years before birth is significant at the 10% level in the regression on anemia. However, the sign of the coefficient goes in the opposite way of what could threaten our identification. Given that the results for anemia have not been consistent in our previous specification, our focus lies more on the placebo test in columns (1) to (3) which are in line with our expectations.

6 Threats to Identification

6.1 Selective mortality

In this section we discuss a few threats to our identification strategy. Equation (4) will provide the causal estimate of drought on health outcomes only when drought is uncorrelated with any latent determinants of child health. However, there are several threats to this

TABLE 9
Robustness Check, Lags of Droughts

	(1) WAZ	(2) WAZ <-2	(3) WAZ <-3	(4) Anemia
Drought t-1	-0.116***	0.020**	0.022**	-0.001
	(0.038)	(0.009)	(0.009)	(0.006)
Drought t=0	-0.091***	0.018**	0.012*	0.002
	(0.026)	(0.007)	(0.006)	(0.005)
Drought t-2	-0.064	0.012	0.010	-0.012*
	(0.039)	(0.010)	(0.009)	(0.006)
Drought t-3	-0.058	0.005	-0.002	-0.008
	(0.038)	(0.010)	(0.008)	(0.007)
Child's age	Yes	Yes	Yes	Yes
Birth quarter f.e.	Yes	Yes	Yes	Yes
District f.e.	Yes	Yes	Yes	Yes
Observations	155,937	155,937	155,937	158,547

Notes: Notes: Robust standard errors, clustered at district level, are in parentheses. Col 1-2 report OLS coefficient from a general multiple linear regression model while Col 3-8 report OLS coefficient from a linear probability model. **Controls**: Gender, schedule caste/tribe, father literacy, mother literacy, religion (indicator for hindu), poverty (indicator of low standard of living index), birth order, age in month, year of interview, quarter of birth f.e., district f.e.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

identification. First, the composition of children may change due to selective mortality. If weaker fetuses or children are culled due to drought, the pool of surviving children observed in the sample are positively selected one with better health. This will bias our estimate in the downward direction understating the true negative effects of drought (Currie, 2009).[13]

6.2 Selective migration

The second concern originates from selective migration. If a household migrates to another district after the individual's birth, the assumption that the current district of residence is equivalent to the district of birth is violated. In case migration is selective, meaning that individuals who migrate from drought-prone districts are more healthy and well educated

[13]The birth weight literature has consistently discussed the fetal selection concern due to "culling of the weakest (Currie, 2009)".

than those who stay and that they immigrate to a district where there was no drought prior or in the child birth year, the estimated results will be biased. More specifically, the in utero or drought in the year of birth dummy will be coded "0" when it has to be coded "1". The definition of our drought variable partly addresses this concern. Droughts are defined by year-to-year variation in rainfall within a district and are not affected by differences in rainfall levels between districts, which in turn is plausibly much more decisive for migration decisions than within district rainfall variation.

Unfortunately, the DLHS survey does not contain information on migration. The 2004/2005 wave of the Indian Human Development Survey, however, includes questions about the place of origin and the time that the household has been in place allowing to study the migration patterns empirically. We analyzed the IHDS data and found that almost 90% of the rural population has never changed their district of residence. The low mobility in IHDS data generally confirms what has been stated in the literature about migration (Munshi and Rosenzweig, 2009; Topalova, 2010). Following our argumentation above and Shah and Steinberg (2013), we expect the estimated effects to constitute a lower bound of the true effect in the presence of selective migration.

6.3 Selective fertility

Another channel that may bias our results is selective fertility in response to drought conditions. Pitt (1997) argues that selective fertility can emerge when parents base their fertility decision on the perceived health status and survival probability of children. Children may differ in their health not only with genetic endowments and characteristics of the household but also with changes in the spatial location, e.g. with droughts. Following Pitt (1997), positive birth selection occurs when parents are less likely to have a child due to the presence of devastating rainfall shocks. Negative selection may also occur if parents decide to have a child after considering the poor environment. Both scenarios would lead to a bias in the estimated coefficients due to sample selection. Shah and Steinberg (2013) discuss the presence of an upward bias due to negative birth selection. However, a downward bias is also possible when parents that are “worse off” due to physical and emotional stress delay fertility while parents with higher abilities to cope with the rainfall shock do not postpone their fertility decision. Once again, the definition of our drought variable partly addresses this concern with the same argument that we made for selective migration.

We try to explore this issue further by looking at the birth cohort size for all years and districts available in the sample. Since the size of the birth cohort is also influenced by fertility patterns, variation in the cohort size captures miscarriages and the effects of selective fertility.[14] We run a regression of the log of the birth cohort size for every year and district on drought in the year of birth and for 5 years before birth. Standard errors are clustered at district level and additional controls for year of birth and year of birth squared are added as well as district fixed effects. As in the previous specifications, the samples are restricted to include only observations from rural areas. The coefficient for drought in t-5 and t-6 are positive (table A.1 in the appendix). The latter is, however, only marginally significant. Hence, there is no indication for systematic changes in the cohort size due to the presence of deficit rainfall supporting the evidence that there is no selective fertility or mortality through miscarriages.[15]

7 Discussion

This study attempts to test the Barker’s fetal origins hypothesis by using weather shock as an exogenous event in rural India. Weather shocks are defined as deficit rainfall years modeling drought condition in the year and district of birth. We find that exposure to a drought in-utero has adverse effects on early child health. Children exposed to a drought in utero have an increased probability of lower weight-for-age z-score, and a higher likelihood of

[14]Note that the size of the cohort is also influenced by abortions. However, there is no reason to believe that this behavior would vary in the presence of rainfall shocks and can be neglected in this context.

[15]No impact on the cohort size would be observed when miscarriages even out an increasing fertility rate. There is, though, no reason to believe that fertility would increase due to droughts.

being underweight and severely underweight. Nonetheless, we do not detect any significant effect of drought on anemia incidence among 0-5 years old children.

We find some evidence of heterogeneity in the effects of rainfall shock on child health outcomes. Consistent with the biological and medical evidence, our results indicate that boys are more susceptible to rainfall shock compared to girls. Furthermore, low caste children suffer more from drought than the high caste children. We perform several robustness check and our main findings remain robust to alternative definitions of drought. In addition to the importance of in utero exposure to drought, we also show that drought in the year of birth is equally important for the physical development of children in early years. While exploring timing of gestation, in utero exposure to drought in the first trimester is the most critical period for growth of the children.

In summary, our study demonstrates that the environmental conditions in the womb are critical for physical development using rainfall shocks in India as a natural experiment. It thus provides further support for Barker's fetal origins hypothesis. For policy makers, the implication of these findings points towards a stronger focus on policies that improve maternal and fetal health, especially given the high variability of rainfall in India, and thus the repeated occurrence of droughts within the country. The analysis by birth quarter allows policy makers to identify children and the gestation period that are most vulnerable to drought related health impairments.

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Figure A.1

Histogram of the Number of Droughts per District, 1995-2005

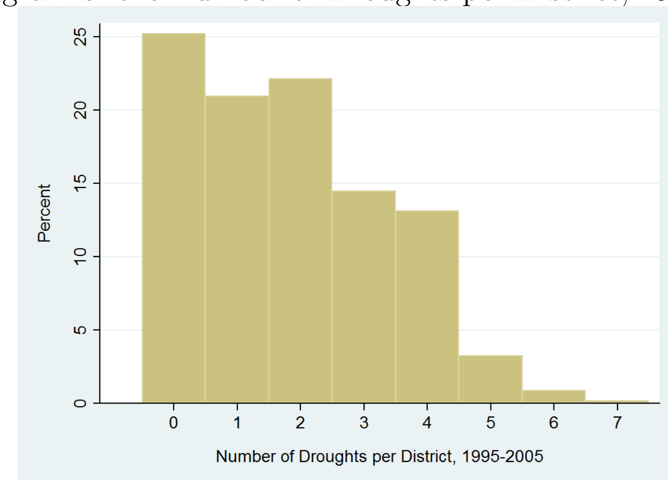


Figure A.2

Droughts per Year in India, 1995-2005

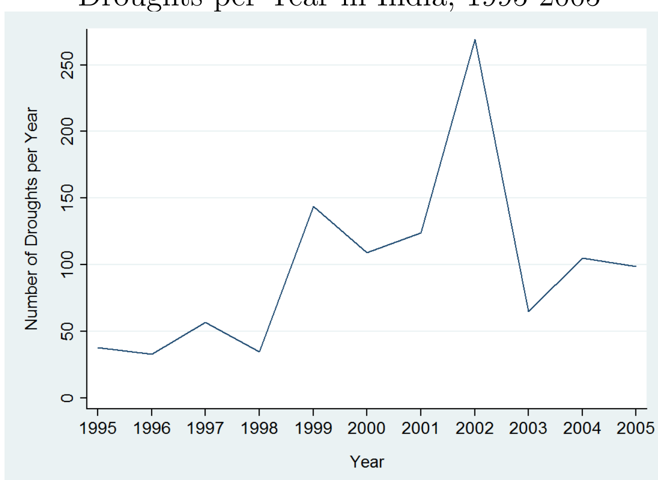
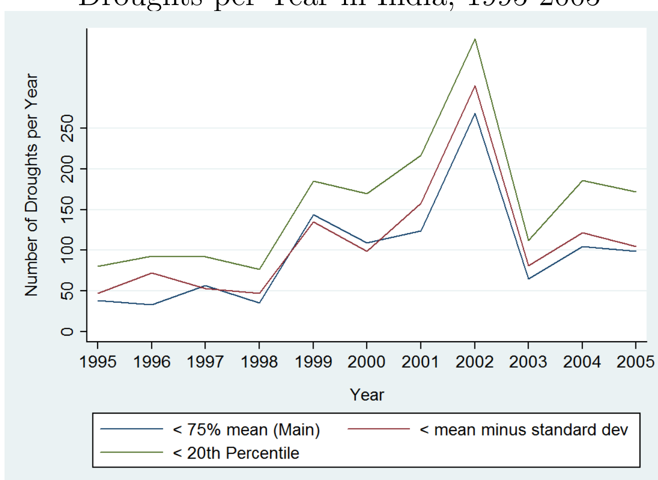


Figure A.3

Droughts per Year in India, 1995-2005



Source: Own illustration.

TABLE A.1

Impact of Droughts on Fertility

	Natural Logarithm of Cohort Size
	Drought Exposure
Drought t=0	-0.153***
	(0.034)
Drought t-1	0.022
	(0.035)
Drought t-2	-0.053
	(0.038)
Drought t-3	0.018
	(0.040)
Drought t-4	0.024
	(0.044)
Drought t-5	0.113***
	(0.042)
Drought t-6	0.072*
	(0.044)
Drought t-7	0.037
	(0.038)
Drought t-8	0.021
	(0.033)
Year of Birth	272.171***
	(10.058)
Year of Birth Squared	-0.068***
	(0.003)
Observations	3689
r2	0.300

Notes: Standard errors are in parantheses. Dependent variable is the ln of the cohort size (the number of children born per year and sitrict). Standard errors are clustered at the district level. Sample is restricted to include only individuals from rural areas. District fixed effects are included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$