DISSERTATION

CLIMATE SHOCKS, ADAPTATION POLICIES, AND HUMAN HEALTH IN DEVELOPING COUNTRIES: AN APPLICATION TO INDIA

Submitted by

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ABSTRACT

CLIMATE SHOCKS, ADAPTATION POLICIES, AND HUMAN HEALTH IN DEVELOPING COUNTRIES: AN APPLICATION TO INDIA

My dissertation is on climate change, policy adaptation, and human health in a low-income nation. Specifically, I focus on the impact of climate change on maternal and child health in India using secondary and spatial climate data. I use an advanced econometric approach to estimate causal effects.

Rural economies in developing countries revolve mainly around agriculture, and many agricultural production operations depend on monsoon rains. Food shortages due to weather-induced crop failure, and the resulting nutritional deprivation can have a negatively impact on maternal and child health. Two of my dissertation chapters are dedicated to understanding the impact of climate change on maternal and infant health. Then there are the drought-relief programs. One is a workfare program, which is very important to the developing world. One of my dissertation chapters explores how the work program may influence the use of contraceptives.

My results suggest that: (1) workfare programs have an effect on the use of family planning methods for rural Indian women; (2) higher soil organic carbon moderates the adverse effect of rain shock on children's health; (3) an early childhood exposure to drought is linked to the prevalence of disability later in life. These results help us understand the impact of climate change on human health in developing countries.

The first chapter shows how providing employment opportunities for women affects their use of family planning methods. Using survey data from rural India, I employ a difference-in-differences strategy and inverse probability of treatment weighting techniques to estimate the causal effects. The results suggest an increase of 2 percentage points (a 3% increase) in the use of modern methods of family planning among currently married women with the introduction of an employment guar-

antee scheme. The use of modern contraceptive methods increased with significant heterogeneity across poor and non-poor households. The findings help inform our understanding of economic development, labor markets, contraceptive use, and fertility.

The second chapter estimates the moderating effect of soil organic carbon content (a measure of soil health) on children's health in response to rainfall shocks in a low-income country setting. Focusing on rural India, I leverage the Demographic and Health Survey data set and high-resolution spatial data on soil organic carbon content and meteorological variables. Using a coarsened exact matching method, I show that a modest change in soil health can provide resistance to wasting in children during periods of low rainfall.

In my final chapter, I estimate the impact of early-life exposure to drought on disability rates in a low-income country setting. Focusing on rural India, I exploit the geographical and cohort variation in drought exposure on the prevalence of disability in later years. The results suggest that early-life exposure to droughts is associated with the prevalence of disability, in particular motor and cognitive impairments later in life.

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Chapter 1

Workfare programs and family planning: The case of MGNREGA

1.1 Introduction

According to the second round of the District Level Household and Facility Survey carried out in 2002-2004, 23 percent of rural Indian married women have an unmet need for family planning.[1] This suggests that women wanted contraception but did not have the ability to acquire it. One reason for not using modern methods of contraceptives could be lack of financial autonomy for women. Public workfare programs such as the Mahatama Gandhi National Rural Employment Guarantee Act (MGNREGA) could give women financial autonomy to access modern method of contraceptives.

Family planning programs and the practice of modern contraception in low- and middle-income countries are crucial interventions to address maternal morbidities (or unsafe abortions) and infant and child mortalities [Miller, 2010, Palamuleni, 2013, Gage, 1995][2]. In addition to reducing maternal morbidity and infant mortality rates, family planning can also foster human capital accumulation for mother and child. For example, Miller [2010] finds that family planning programme interventions promote human capital accumulation including additional years of schooling, a greater probability of working in the formal sector and a lower probability of being married at young ages among women in Colombia. According to the United Nations, contraceptive prevalence is one of the key indicators for measuring improvement in reproductive health and is also one of the indicators of sustainable development goals. According to the 2022 world contraceptive use data sheet,

[1] In particular, 10% of women say they would like to delay their next birth by at least two years and 13% of rural women do not want any children, but do not use any form of contraception. Appendix figure A.1 shows the trend of unmet need of currently married women for family planning.

[2] In the context of India, see also the National Family Planning Programme. Available at: https://nhm.gov.in

the Contraceptive Prevalence Rate (CPR) for women of reproductive age (15-49 years) in India is estimated at 66.7 percent which is marginally higher than Sri Lanka (64.6 percent) and Bangladesh (62.7 percent) in South Asia.[3]

Public workfare programs provide a way for governments to support livelihoods by providing employment opportunities for jobless workers. Public works programs, when implemented well, act as a source of employment and income for the poor and hence raise resilience for citizens [Muralidharan et al., 2017, Sukhtankar et al., 2016]. As of 2015, there were at least 4 prominent public workfare programs around the world concentrated in low- and middle-income countries. These programs provide jobs to people who seek employment, particularly in both post-disaster and post-conflict situations [Subbarao et al., 2012].[4] The MGNREGA is the largest public workfare program in size and ambition. For example, in 2011-2012 the budget was US$ 7.8 billion [Deininger et al., 2016].[5] With the MGNREGA wages being deposited directly to the bank accounts of women, it may lead to increased financial autonomy for women, which in turn may provide opportunity for them to use modern methods of contraception directly and privately.[6] However, the impact of workfare programs on family planning decisions remains largely unexplored in the literature. In this paper, using a nationally representative data set on women's reproductive health in India, I empirically examine if workfare programs affect the use of family planning methods among currently married women in rural India.

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[3] Data is available at https://www.un.org/development/desa/pd/data/world-contraceptive-use

[4] Examples includes the Mahatama Gandhi National Rural Employment Guarantee Act (MGNREGA) in India, the Productive Safety Net Program (PSNP) in Ethiopia, the Programa de Jefes y Jefas de Hogar in Argentina, and the Rwandas's Vision 2020 Umereng Program.

[5] In past, developing countries have used public workfare programs to uplift poor people out of poverty. For example, the Maharashtra Employment Guarantee Scheme in India, 1975-89, and Food for Work Program in Bangladesh, 1987-88, have provided major relief in response to drought and famine [Ravallion, 1991].

[6] In 2012, the Government of India, mandated that MGNREGA wages be deposited directly to the bank accounts of workers to avoid corruption and leakages. Available at https://nrega.nic.in/Circular_Archive/archive/ Operational_guidelines_4thEdition_eng_2013.pdf

Given the policy relevance of the public works program, a sizeable literature exists studying a wide array of outcomes.[7] Despite this, the literature has been limited in considering the aspects of workfare programs related to women empowerment. There are a few studies in low- and middle-income countries that have examined the direct relationship between work status of women and their contraceptive use. Gage [1995], found that, in Togo, women who work outside the home for cash are significantly more likely to use modern methods of contraception. While the correlation between women economic power and contraceptive use has been established in the literature, the evidence that women who work outside the home for cash have a higher contraceptive prevalence rate has yet to be causally studied. This paper builds on two large strands of literature: the impact of workfare programs on labor market outcomes and the family planning decisions within households in low- and middle-income countries.

Labor market opportunities and fertility decisions are endogenous for a number of reasons. For example, women who want to have lots of children may not be motivated to get advanced degrees which will open doors for them in labor force, while women who are career-oriented often have to delay childbearing as they get their careers going. This study uses the employment guarantee program in rural India as an exogenous source of variation in labor market opportunities to investigate how that can impact fertility decisions and contraceptive use.

To estimate a causal impact of the employment guarantee scheme on women's family planning decisions, I use data from the largest demographic and health surveys carried out in India, the District Level Household and Facility Survey (DLHS). I exploit the phased roll out of MGNREGA at the district level within a difference-in-difference (DiD) model. I show evidence of parallel trends. Because the MGNREGA roll out was targeted rather than randomly, it is difficult to find

[7] Human capital accumulation [Ajefu and Abiona, 2019]; on health [Chatterjee and Merfeld, 2021, Chari et al., 2019, Dasgupta, 2017]; on conflict [Fetzer, 2020]; on agricultural productivity[Varshney et al., 2018, Gazeaud and Stephane, 2020]; and on labor market [Azam, 2011, Imbert and Papp, 2015, Zimmermann, 2012, Muralidharan et al., 2017, Berg et al., 2018, Deininger et al., 2016, Merfeld, 2020].

a credible counterfactual.[8] I overcome this challenge by using the inverse probability of treatment weighted technique [Hirano et al., 2003].

Results suggest that married women in rural districts increased their use of modern methods of family planning after the introduction of an employment guarantee scheme. The mean increase is about 2 percentage points. The use of modern contraceptive methods increased with significant heterogeneity across poor and non-poor households. I find that married women aged 35 years and above from poor households are driving the results. I also find that MGNREGA allowed young women to postpone their first birth by 0.11 years on average. This is an important result in the context of birth timing and child quality. Intra-household bargaining, financial autonomy for women as well as additional household income are likely mechanisms of impact. My study provides new evidence on the impact of public works on the use of family planning methods.

1.2 Institutional background

1.2.1 National Rural Employment Guarantee Act

The National Rural Employment Guarantee Act (NREGA) established in 2005 had a primary objective to enhance the livelihood security of the households in rural areas of India by providing at least 100 days of guaranteed minimum wage employment in every financial year to each household whose adult members volunteer to do unskilled manual work.[9] The program was renamed to the Mahatma Gandhi National Rural Employment Guarantee Act in 2009.

The conditions of rural employment guaranteed by the MGNREGA include: (a) the adult members of each household who live in rural areas and are willing to do unskilled manual labour may submit their names, age and household address to the village governing body (*Gram Panchayat*) at

[8] MGNREGA was first rolled out in the less developed districts based on the algorithm developed by the Indian Planning Commission, 2003.

[9] According to the National Rural Employment Guarantee Act, 2005, Ministry of Rural Development, Government of India, public works includes (a) water conservation and water harvesting; (b) drought proofing (including afforestation and tree plantation); (c) irrigation canals including micro and minor irrigation works; (d) renovation of traditional water bodies including desilting of tanks; (e) land development; (f) flood control and protection works including drainage in water logged areas; and (f) rural connectivity to provide all-weather access.

the village level for the issue of a job card; (b) each adult member who has a job card is guaranteed employment for up to 100 days in a given fiscal year within 15 days of the request for work; (c) a minimum of 14 days of continuous employment with no more than 6 days per week; (d) at least a third of the beneficiaries must be women with wages equal to those of men.

The central government shares the major cost of the program: the payment of wages, and up to three-fourth of the material costs of the public works. The state government is liable for the unemployment allowances and one-fourth of the material costs of the public works.

The scheme was rolled out in three phases across three years (2006, 2007 and 2008). In the first phase, 200 districts were included in the scheme, and 130 and 270 districts were included in the second and third phase respectively. The roll out was not random. The scheme targeted poor districts first. Critical to the empirical strategy of this article is the way MGNREGA was rolled out. I exploit this variation in implementation timing to estimate the impact of MGNREGA on the use of family planning methods among currently married women. Figure 1.1 shows a map of the three phases of the scheme roll out.

According to the Ministry of Rural Development, Government of India, women constituted 54.59 percent in 2018-19, 54.78 percent in 2019-20, 53.19 percent in 2020-21 and 54.54 percent in 2021-22, an increase in women's participation in MGNREGA from 40 percent in 2006-07.[10] Existing evidence suggests that the MGNREGA had far reaching impacts. For example, [Shah et al., 2015] show that women's share of work under MGNREGA is greater than their share of work in the labor market across all states.[11] These findings suggest that MGNREGA had higher effects on employment for rural women than it was for rural men.

1.3 Why MGNREGA may increase the contraceptive use?

This section provides insight into why MGNREGA may influence contraceptive use. I use MGNREGA's mandate to give women work to study the relationship between women working for

[10]Available at https://rural.nic.in/en/press-release/participation-rural-women-mgnregs

[11]Available at https://nrega.nic.in/Circular_Archive/archive/MGNREGA_SAMEEKSHA.pdf

money and their use of contraceptives. Figure 1.2 summarizes the various mechanisms through which the MGNREGA affects women's use of family planning methods.

First, MGNREGA may normalize work outside the home for women, this can decrease the stigma often associated with working outside the home [Jensen, 2012]. Fewer Indian women work away from home for pay because of a number of factors including high transaction costs and social stigma [Jensen, 2012]. Jensen [2012] in his seminal paper shows that rural Indian women who work away from home for pay delay marriage and childbearing. MGNREGA may lower such costs associated with working outside home by making work available in their villages. For example, Reddy et al. [2014] show that female workforce participated in MGNREGA in large numbers compared to other programs

The arrival of MGNREGA increases family income, and it does so disproportionately for women [Zimmermann, 2012]. Zimmermann [2012] finds that MGNREGA increased female wages in the private sector. Greater household income overall can also relieve budget constraints that may prevent households from purchasing contraceptives they would like to use. This is one pathway through which MGNREGA influences women's use of contraception.

Higher incomes for women, as well as greater financial autonomy, can also increase women's bargaining power within the home, allowing household decisions to better reflect their preferences. For example, Anderson and Eswaran [2009], in Bangladesh, demonstrate that women working outside the home have a greater bargaining power to make reproductive decisions. Women's economic power that involves increased bargaining power leads to attitudes towards negotiating safer sexual relations with the husband and the intention to use family planning services [Gage, 1995, Hogan et al., 1999]. Therefore, women's economic empowerment may reduce their reproductive health vulnerabilities [Westeneng and d'Exelle, 2015] and is another pathway through which MGNREGA influences women's contraceptive use.

In summary, MGNREGA may increase the contraceptive use among rural women because of the following reasons: first, MGNREGA wages may improve the bargaining power of women and hence may lower the cost of negotiating sexual activity and fertility choices with men; Second, MGNREGA wages add to income within the household that may relax the budget constraint and the purchase of modern methods of contraceptives may be possible; and third, MGNREGA contributes to the financial autonomy among rural women as the MGNREGA wages are deposited directly to their bank accounts and thus the use of modern method of contraceptives directly and privately.

Overall, these different mechanisms lead to some specific tests for heterogeneity. For example, if greater bargaining power and financial autonomy drive the results, we expect impacts to be strongest in areas with highest female participation rate in the program. Family planning decisions can also be affected by household characteristics, such as religious and social groups (castes and tribes). Maybe some religious or social groups have a greater reluctance towards family planning programs. We also take household characteristics into account in our analysis.

1.4 Data and Empirical Strategy

This section details the data used in my analysis as well as my strategy for estimating the causal effects of MGNREGA on women's family planning decisions.

1.4.1 Data

I use the District Level Household and Facility Survey (DLHS) collected by the Ministry of Health and Family Welfare, Government of India to study the women use of family planning methods. The DLHS is one of the largest demographic and health surveys carried out at regular intervals in India. The DLHS data sets are available from the International Institute for population Sciences. In rural areas, DLHS employs a two-stage (many villages in a district) stratified probability proportional to size sampling design.[12] Households are primary sampling units in the DLHS. I use rounds 2 and 3, collected in 2002-2004 and 2007-2008.[13] The surveys are repeated cross-sections which cover detailed questionnaires on topics of maternal and child health, family planning and other

[12]More information about the DLHS sample selection is obtained at rchiips.org

[13]DLHS-2 reference period is from January, 1999-2001 to survey date and DLHS-3 reference period is from January, 2004 to survey date

reproductive health services. The DLHS round 2 (2002-2004) is pre-treatment year and the DLHS round 3 (2007-2008) comes after the implementation of the first phase of treatment and before the implementation of third phase. I apply Inverse Probability of Treatment Weighting (IPTW) to match district characteristics. I then exploit the variation in timing of the treatment to employ a difference-in-differences (DiD) estimator. This DiD strategy compares the outcomes in households in districts included in first and second phase (Early) to the households in districts in third phase (Late).

1.4.2 Family Planning Methods

This section reviews the contraceptive methods available to women in the sample and their characteristics.

The dependent variable used in the analysis, any family planning methods use, was obtained from a question in the section-IV on contraception and fertility preferences in the individual woman's questionnaire. Women were asked the question: Are you/your husband currently doing something or using any method to delay or avoid getting pregnant? If the woman reported that she was using any method, she was coded 1; If she reported she was not she was coded 0.

To make analysis and interpretation simpler, I regroup some variables into modern and traditional family planning methods. Modern methods include permanent contraceptives, such as female and male sterilization; Long-acting reversible contraceptives (LARCs), such as injectables and intrauterine devices: IUD/Copper-t/Loop; and Oral pills, female condom and a male condom (*Nirodh*). Traditional methods include the use of rhythm, periodic abstinence, and withdrawal.

Modern methods of contraceptives including oral pills, and female and male condoms do not require medical prescriptions and can be available over-the-counter but may require husband and or family members (especially the mother-in-law) approval, for example in the case of sterilization. Not all modern methods are easily accessible in rural areas depending on the socio-culture norms and the community access to health care services specifically in the case of LARCs. None of LARCs methods require the knowledge or consent of husband. There may be concern for supply constraints in rural areas of the country. For example, it is possible that birth control supplies changed at the same time as MGNREGA. However, according to the third round of the DLHS (2007-2008), only less than 4% of contraceptive users in rural India ever faced difficulty in getting any methods of family planning. This provides suggestive evidence that supply is rarely the constraining factor in observed use of contraceptives. We also know of no national level program expanding contraceptives supplies that systematically correlated with the roll out of MGNREGA.

According to the DLHS-3 (2002-2004), about 43 percent of contraceptive users obtained contraception from government hospitals, followed by primary health centres and pharmacies and private hospitals (43%, 15% and 10%, respectively). Among the members of rural Indian households that have ever used contraceptives, a little less than three-fourths have paid money in 2007-2008 for pills, female and male condoms, and injectables. Therefore, MGNREGA wages would allow the purchase of contraceptives.

1.4.3 Inverse probability of treatment weighting

Following Gazeaud and Stephane [2020], I use the logit estimator to compute the inverse probability of treatment weighting:

$$Treated_d = \beta_0 + {X_d}'\beta + \varepsilon_d \tag{1.1}$$

where X_d is a vector of district-level variables. As mentioned earlier, roll out was targeted at poor districts which were defined on the basis of variables at the district level. Following Zimmermann [2012] and Merfeld [2020], I include total population, percent rural, area (in square km), percent scheduled castes, percent scheduled tribes, percent literate, average monthly per capita consumption expenditure (2004-2005 prices), average casual wage (2004-2005 prices), labor force participation rate, female labor force participation rate, rainfall, and growing degree days.[14]

[14] Appendix Table A.14 shows the data sources used in the analysis.

I use logistic regression to calculate the propensity scores and then derive the inverse probability (IP) of treatment weighting. The IP-weight is then used as a weight in the equation 1.2. Appendix Table A.1 shows the logistic regression predicting treatment.

Figure 1.3 shows the distribution of propensity score by treatment groups. The area within the dashed line represents the common support. The highest propensity score for untreated is 0.9636089 and the lowest propensity score for treated is 0.044275.

Table 1.1 shows the IP-weighted summary statistics for district characteristics used in the analysis. The labor force participation rate is higher in the comparison districts. In particular, the labour force participation rate for women is higher in the comparison districts. The p-value in column 3 of Table 1.1 indicates that district-level variables do not systematically differ across treated and untreated districts.

Descriptive Statistics

In the second round of the DLHS (2002-2004), data were collected on 507,622 eligible women aged 15 to 44 who are currently married and whose marriage has been consummated. In the thrid round of the DLHS (2007-2008), data were collected on 643,944 ever-married women aged 15 to 49 and 166,620 unmarried women aged 15 to 24. From this data, I focus on the sample of currently married women aged 15 to 44 whose marriage was consummated to compare the outcomes of interest with other surveys. For the purposes of my analysis, I exclude currently pregnant women from the sample. The analytical samples include 292,810 currently married and fertile women aged 15-44 years living in rural India in 2002-2004, and 350,210 such women in 2007-2008. Under the MGNREGA Act, 2005, individuals 18 years of age or older are eligible to work under the program. Therefore, I restricted the sample to people 18 years of age and older.

Table 1.2 presents the individual summary statistics, IP-weighted, by treatment groups. More than a third of women currently married in treatment and untreated districts used family planning methods. About 48% of women currently married in the treated districts used modern contraception and about 41% in untreated districts. Fewer than 10% of currently married women used traditional contraceptive methods in both treated and untreated districts. In my sample, women's sterilization is the most common modern method and men's sterilization is the least common method of contraception. Oral pills, and male and female condoms remain very low at less than 8% in rural areas. Intrauterine device (IUD) for currently married females is less than 5% in both treated and untreated districts. The traditional method of contraception in my sample is about 12% in treatment districts and about the same in untreated districts. In summary, modern methods of contraception are few in number in rural areas and are intended for women. Appendix Table A.2 presents individual summary statistics before the match.

While there are many variables that may influence contraceptive use, for the purpose of my analysis I focus on women's age, reading or writing ability, number of surviving children, social groups and religion. On an average, the age of women is about 30 years and half of them can read or write. A little less than three-fourth of husbands in the sample can read or write. Percent of households belonging to the scheduled castes or tribes - marginalized section of the society - are 35% in treated districts and 39% in untreated districts. Married women in rural areas bore, 3 children, on an average, in both treated and untreated districts. About 42% (respectively, 39%) of modern methods of contraception are used by married woman under the age of 35 years in treated (respectively, untreated) districts. About 62% (respectively, 55%) of modern methods of contraception are used by married women aged 35 years and older in treated (respectively, untreated) districts.

1.4.4 Econometric Specification

I present reduced-form estimates of family planning decisions by exploiting the roll out of MGNREGA at the district level within a difference-in-difference model.

$$y_{ihdt} = \beta_0 + \beta_1 MGNREGA_d {*} Post_t + \xi_{ihdt} + \alpha_d + \phi_{st} + \lambda_{mt} + \varepsilon_{ihdt} \tag{1.2}$$

where y_{ihdt} is the use of family planning methods for individual i in household h in district d at time t; $MGNREGA_d$ is the dummy variable, 1 if public workfare program is available in district d; $Post_t$ is a dummy variable indicating that the observation is from the 2007-2008 round; ξ_{ihdt}

includes a set of individual and household-level controls. Individual characteristics include age of women, age at first birth, education. Household characteristics include religious and social groups. α_d are district fixed effects, which control for time-invariant characteristics of each district which impact the use of contraceptives; ϕ_{st} are state-year fixed effects which controls for common shocks at the state level across time; λ_{mt} is month and year of the interview fixed effects; and ε_{ihdt} is the error term. I estimate this specification using weighted-least-squares, where the weights are determined by the inverse probability of treatment weighting techniques. Weighted Least Square (WLS) estimator is used for all regressions. I cluster the standard errors at the level of treatment (district).

The coefficient of interest is β_1, which measures the average effect of MGNREGA on the outcome of interest and is interpreted as the intention to treat (ITT). Because in the DLHS dataset, I do not observe who participated in the MGNREGA.

Threats to identification

The major threat to identification is that confounding variables that determine treatment may also affect the outcome variable. By including additional observable controls in main Equation 1, I take into account the observale confounding variables but there may still exist unobserved confounding variables that could bias coefficient estimates. I go into detail on the main threats to identification and others.

As the MGNREGA program was targeted toward poor districts rather than randomly allocated, finding a credible counterfactual is difficult. So, the first threat to identification arises from non-random assignment of treatment districts. In the absence of a credible counterfactual, the treatment and control groups may not be equivalent in their characteristics and, therefore, a simple difference in the outcome variable may bias the estimates. In literature (e.g., Merfeld [2020]), the above concern was addressed by including the variables used to rank districts - the proportion of scheduled castes/tribes, the agricultural productivity, and the agricultural wages - on the right hand side of the econometric equation. I use IP-weighted matching methods to match district characteristics in the main econometric specification. The IP-weighted technique is a propensity score-based method which aims to achieve a balanced distribution of confounding factors across treatment groups. The result is more robust and produces less biased estimates of the impact of treatment[Allan et al., 2020]. Matching reduces selection bias, but does not remove it entirely because I limited to matching on observable variables. Therefore, changes in other confounding factors that could produce a deviation from parallel trends could remain. Coefficient stability with and without controls provide suggestive evidence that omitted factors are not driving results. For example, if coefficient estimates do not vary with and without controls, then the omitted variables would have to correlate with the arrival of MGNREGA and not the included controls [Schlenker et al., 2007].

Second, there is a concern that districts with greater female labour force participation already expect to use family planning methods. I address this concern by including the term triple interaction MGNREGA*Post*High female LFPR into the main specification. I construct a dummy variable of the high female labour force participation rate (LFPR), 1 for values higher than or equal to the average of the female LFPR and 0 for the others.[15] Appendix Table A.3 presents the effect of MGNREGA on women use of family planning methods by female labor force participation rate. The coefficients are insignificant at the 5 percent significance level, suggesting that there is no impact on my findings.

As mentioned before, the MGNREGA rollout was in multiple time periods and thus differential timing design might introduce bias. Unfortunately, the rounds of DLHS does not match with the timeline of program rollout and hence I cannot test the heterogeneous treatment effect with multiple time periods.

However, I am able to test for heterogeneity across implementation phases with the dataset used in this analysis. Figure 1.5a and 1.5b shows the pre-program trends for any family planning methods and any modern methods across MGNREGA implementation phases. We see that the parallel trends in the pre-treated period hold.

[15]The sample used to identify the districts with a higher women workforce participation rate includes both the urban and the rural residents whereas, the MGNREGA is implemented only in rural areas.

Furthermore, Figure 1.6a and 1.6b shows the differential effects of MGNREGA for any family planning methods and any modern methods, respectively. Phase 1 districts had one additional year of implementation than districts in phase 2. As a result, we see that any family planning methods is positive and statistically significant for districts in phase 1.

Pre-Program Trends

The identification strategy requires that the trends in outcomes of the treatment group moves in parallel with the comparison group prior to the implementation of MGNREGA. Figure A2 in the appendix shows the pre-program trends for two family planning methods using Rounds 1 (1998-1999) and 2 (2002-2004). There is evidence to support a parallel trend in contraceptive outcomes of interest.

To support the parallel trend assumption, I re-evaluate Equation 1.2 but use Round 2 (2002-2004) as post and Round 1 (1998-1999) as pre-program. Table 1.3 presents the placebo analysis. The coefficients are nonsignificant at the 5 percent significance level suggesting that pre-treatment trends are not driving the results. Moreover, the coefficients for falsification test on any current use of contraception and the use of modern methods of contraception is opposite sign relative to the main treatment effect. This may raise a concern for mean reversion, but the size of the coefficients is small and hence not a serious problem for the purposes of my analysis. The placebo test excludes the possibility that MGNREGA was adopted in districts where birthrates were already increasing.

I provide further evidence of parallel trends. I include rounds 1-3 in a single specification and do an event-study in addition to the traditional DiD. The specification for an event-study regression is given by

$$y_{it} = \sum_{j=-2, j\neq -1}^{1} \beta_j int_{it}^{j} + \alpha_d + \phi_{st} + \lambda_{mt} + \varepsilon_{it} \tag{1.3}$$

where j denotes leads and lags of the event of interest. int_{it}^{j} represents an interaction term between year and treatment. The terms are defined as in Equation 1.2.

Figure 1.4a and 1.4b shows an event-study regression for any family planning methods and any modern methods, respectively. We see no evidence for non-parallel trends in pre-treated period.

1.5 Results

Table 1.4 presents the main results from equation 1.2 using IP-weighted and restricted to the common support region (See Table A.5 in the Appendix for unweighted results.).[16] The results suggest an increase of 1.8 percentage points (approximately 3% increase) in the use of family planning methods in treated districts. Specifically, the use of modern methods shows an increase of 1.4 percentage points (approximately 3% increase). The point estimate for any traditional methods of family planning is not different from zero. Refer to Appendix Table A.7 for the impact of MGNREGA on the use of family planning methods for women under the age of 18. Furthermore, I report the regression results for various econometric specifications in Table A.6 in the appendix.

As mentioned in the data section, the distribution of propensity scores for treated and untreated are skewed. This may arise from the presence of very high propensity scores for untreated and very small propensity score for treated and may influence the estimates. The trimming process addresses the above concern by removing very high and low propensity scores from the sample. Appendix Table A.4 presents the effect of trimming at the fifth centile on the IP-weighted estimate. The results remain the same.

Table 1.5 presents the disaggregated types of modern contraceptives. The permanent contraceptives includes female and male sterilization and reversible contraceptives includes IUDs/Copper-t/Loop, oral pills, male and female condoms, and others. Panel A shows the use of modern contraceptives for married women aged under 35 years. In Panel A, all coefficients are positive with small size and nonsignificant at the 5 percent significance level. Panel B shows the use of contraceptive use for married women age 35 and above. The results suggest that MGNREGA has a positive association with the use of reversible contraceptives for married women aged 35 years and older. The mean increase is 1 percentage point. The point estimate is significant at 5 percent significance level. This shows that the married women aged 35 years and older are the most impacted by MGNREGA in regard to the use of modern methods of contraceptives. I also compare this using an interacted model. Table A.8 in the Appendix presents results after including the triple interaction

[16] About 10% of data is excluded when restricted to common support.

term MGNREGA*Post*Age 35 and above in the main specification. I construct a dummy variable for married women aged 35 years and older. The findings are unchanged. See Appendix Table A.7 for the effect of MGNREGA on the use of family planning methods below the age of 18.

Next, I show how MGNREGA's availability is associated with the timing of a woman's first birth. Table 1.6 reports the impact of MGNREGA on women's age at first birth. The results suggest an increase in women's age at first birth in treated districts by 0.11 years or 1.32 months. This finding implies that MGNREGA may have raised the costs of the first birth. These costs may include forgoing desired sexual activity and negotiating sexual behaviour and fertility with husbands [Miller, 2010]. This demonstrates that putting money in women's hands empowers them to negotiate family planning decisions within a household.

Then I examine the impact of the MGNREGA on the accessibility of contraceptives by including the term triple interaction MGNREGA*Post*High share of contraceptive use in the main specification. I construct a dummy variable of the high share of contraceptive use, 1 for values above the average of all modern contraceptive use in a district and 0 for others. The share of contraceptive use reflects the availability of contraceptive use at the district level. Appendix Table A.9 presents the effect of MGNREGA on women's use of family planning methods, in proportion to contraceptive use. The coefficient for any traditional methods of contraceptives is negative and statistically significant at the 10 percent significance level, suggesting that the introduction of MGNREGA decreased the use of traditional ways of contraceptive. The coefficient for any modern methods of contraceptive is also negative but statistically insignificant at 5% significance level. The coefficient for any methods of contraceptive use is negative and statistically significant at 5% significance level. The joint coefficient for the effect of treatment and the effect of treatment for a high proportion of contraceptive use becomes zero. The overall findings suggest that women have reduced the use of traditional methods of contraception in treated districts than non-treated districts. However, the results indicate no impact of the program on modern methods of contraception.

The results are robust to a number of robustness checks. First, I perform a matched DID with coarsened exact matching algorithm. Second, as the dependent variables are binary, I use the probit specification to estimate the impact of MGNREGA on the use of family planning methods. Third, I include the estimated propensity score of being in the treated district on the right hand side of the main regression equation 1.2 as an additional variable. Tables A.10, A.11 and A.12 in the appendix provide the respective results. The findings are unchanged.

As mentioned previously in the empirical strategy section, I combined Phase 1 and Phase 2 districts to build treated districts. In order to explore if this is of concern, I investigate the differential effects of MGNREGA across phase 1 and phase 2 on the use of family planning methods. Table 1.7 reports how the results differ across treated districts in phase 1 and in phase 2. The results show an impact of MGNREGA on the use of modern methods of contraception for married women in the districts treated in phase 1. I find no effect for the districts treated in phase 2. This suggests that the impacts take time. In addition, I fail to reject the equality test of DID estimate across phase 1 and phase 2. Therefore, the results provide no evidence of differential effects of MGNREGA in the Phase 1 and in Phase 2 districts.

1.5.1 Extended results

Heterogeneity by star states

There exists enough evidence in literature highlighting a large heterogeneity in the implementation of MGNREGA. The heterogeneity exists in key features of implementation such as access to works, the efficiency of payments, corruption, work site facilities and projects [Sukhtankar et al., 2016]. Dutta et al. [2012] shows rationing in public works, not all rural households that demand paid work gets work. For example, in 2011-12, the share of households that demanded work (total households demanded work in a district divide by total rural households in that district) was 33 percent, on average, at the national level. Only about 4 percent of share of households reached 100 days limit of work. For about 29 percent of share of households that demanded work there was not enough work was available[17].

Imbert and Papp [2015] have identified states that have shown comparatively better performance and classified them as star states[18]. I expect MGNREGA in star states to have a larger effect on women use of family planning methods. I follow the same classification in my analysis. Table 1.8 presents the results on star states. The sign on coefficients for the modern family planning methods is positive but nonsignificant at the 5 percent significance level.

Heterogeneity by wealth index

The MGNREGA is a poverty-alleviation program whose main objective is to increase the well-being of low-income households. But middle- and high-income households can participate in the MGNREGA program. For example, Dutta et al. [2012] found that non-poor households participated in the MGNREGA in response to the agricultural productivity shock, such as the rainfall shock.

To estimate heterogeneity by wealth index, a composite measure of a household's cumulative standard of living, I split the data into low, medium, and high wealth indices. I observe the Wealth Index variable in the DLHS Dataset. About 58, 30, and 12 percent of the sample in DLHS-2 (2002-2004) falls into the category of low, middle, and high life indexes, respectively. About 41, 37, and 22 percent of the sample in DLHS-3 (2007-2008) falls into the category of low, middle, and high life indexes, respectively.

Table 1.9 reports the results. Panel A presents the results of women from low-income households. The results suggest a 3 percentage point increase (a 6% increase) in family planning methods with the introduction of MGNREGA. Due to MGNREGA wages, low-income women can afford the high upfront costs of contraceptives, especially LARCs, such as intrauterine devices. I also see

[17] Own calculation based on MGNREGA Public Data Portal for FY: 2011-12 (available at MGNREGA Public Data Portal; website: nregarep2.nic.in)

[18] Star states include Andhra Pradesh, Himachal Pradesh, Madhya Pradesh, Chattisgarh, Rajasthan, Uttarakhand, and Tamil Nadu [Imbert and Papp, 2015]

effects for high-income women, as shown in Panel C. This may be because of an income effect that prioritizes the quality of investment in a child. The effect is relatively lower, 2 percentage points, for high-income households.

Panel B presents the findings of women associated with middle-income households. Point estimates are positive and suggest an increase in family planning methods. But the coefficients are not significant at the 5% significance level.

I also compare this using an interacted model. Table A.13 in the appendix presents results after including the triple interaction term MGNREGA*Post*Poor in the main specification. I construct a dummy variable for a low-income household. Poor is coded as 1 for low wealth and 0 if not. The results indicate that the use of contraceptives by women in both poor and non-poor households is statistically different.

1.6 Discussion and Conclusions

This paper examines the impact that workfare programs have on family planning decisions within households. Exploiting the rollout of MGNREGA at the district level within a difference-in-difference model I document that MGNREGA increased the use of any family planning methods by 1 percentage point (15% increase) among married women aged 35 and older. The effect of treatment is significant for poor as well as rich households. The impact is greater among poor households (about 6%). Column 2 of Table 5 shows that MGNREGA has increased the use of reversible contraceptives in married Indian women aged 35 and older. The MGNREGA program may have helped women who have reached their peak of fertility (aged 35 and over) achieve the desired level of fertility by increasing their use of contraceptives. This has important economic consequences because women with contraception remain in the labor market after reaching the desired fertility. In addition, the woman's age at first birth increased by 1.3 months from the 19.36-year-old sample mean with the introduction of the MGNREGA program. These findings can be implied to empower women improve their reproductive health. The ability to acquire modern methods of contraceptives can result in fewer births for women in their lifetime. Fewer children improve the quality of investment in comparison with more children. Overall, the results of the paper provide new evidence and inform policy makers and implementer about the impact of MGNREGA on women's empowerment.

One contribution of my article is to offer a causal relation between work programs and family planning decisions. This study contributes to the literature that demonstrates that providing women with opportunities to generate income affects their reproductive decision-making within the household. Increased family planning methods could address maternal morbidity and negative impacts on child health in rural areas in low- and middle-income countries.

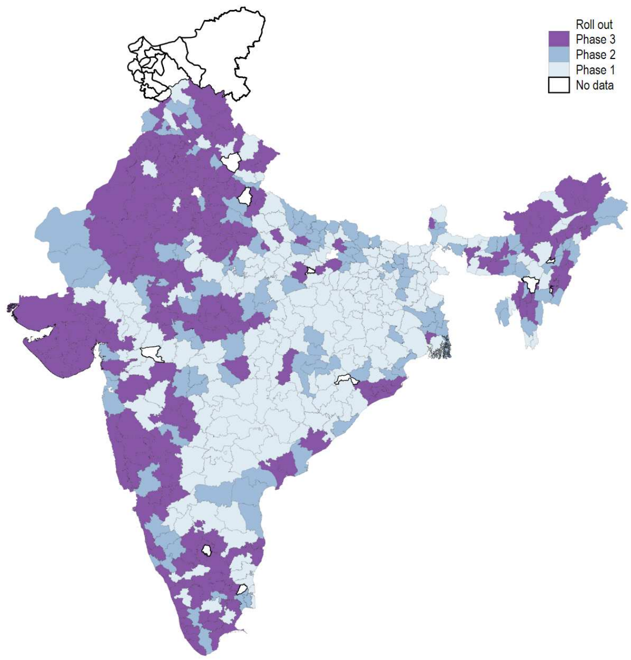
1.6.1 Limitations

The limitations of this study are related to various sources of measurement errors and are as follows: First, reporting on contraceptive use might be inaccurate. That may arise because in traditional societies such as in rural India, the discussion on sex and sex-related subjects is regarded as taboo. Second, my study includes only currently married women in the sample that may bias downward the contraceptive prevalence. Third, cultural setting also influences the reproductive decision-making along with the position of individual women. Therefore, any detailed examination of contraceptive practice requires variables on cultural practices and social norms which are missing in the national datasets including DLHS. For my results, this means that the treatment effect is a lower bound of the true impact.

1.6.2 Future works

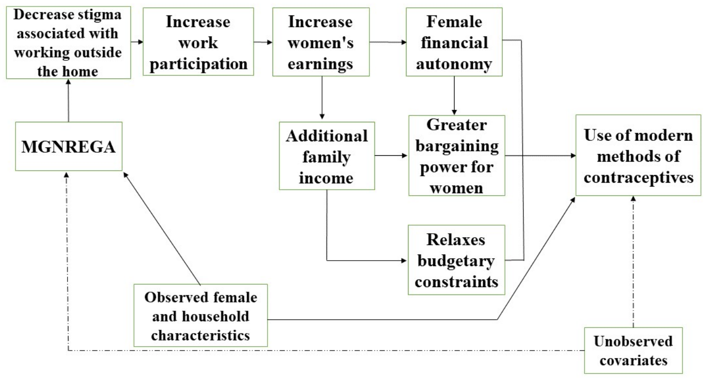
Women's peer groups may influence contraceptive use. A future research idea based on this paper is to explore the spill-over effect of MGNREGA on contraceptive uses. More specifically, research will focus on whether contraceptive choices are influenced by peer groups.

Another idea for future research using the similar framework is to investigate the employment opportunities and breastfeeding practices. Breastfeeding is associated with maternal and child health. Putting money in women's hands could increase household nutrition and encourage maternal breastfeeding practices. Also, working away from home may reduce the contact time between the mother and the child and thus interfere with breastfeeding practices. The empirical literature on this topic is still incipient and requires additional research.



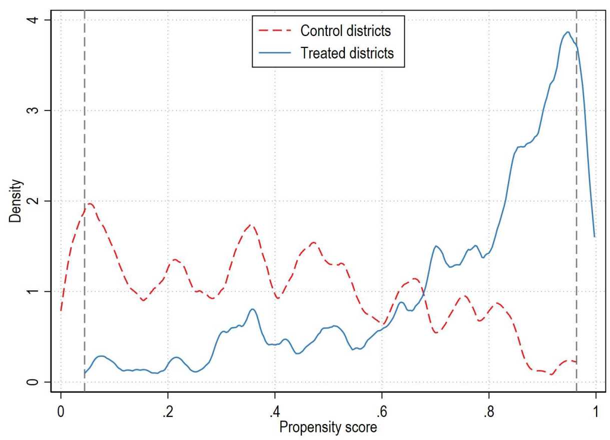
Notes: Rural Indian districts color-coded to distinguish different phases. Source: Own calculation based on 2001 census boundaries.

Figure 1.1: The three phases of NREG scheme roll out.



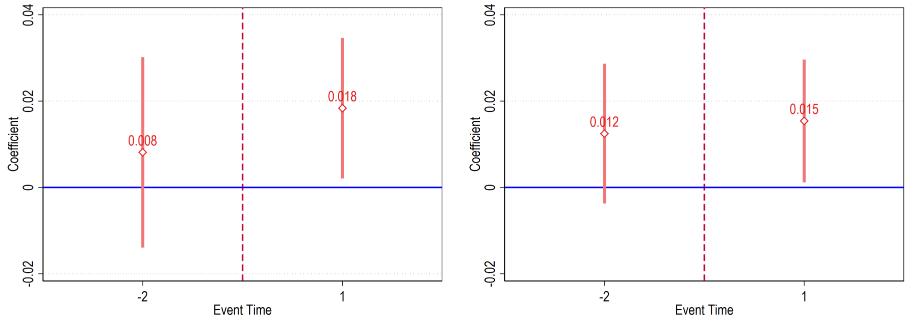
Notes: The figure highlights the different mechanisms through which the MGNREGA, the Job Guarantee Act, empowers women to use family planning methods. Source: Own elaboration.

Figure 1.2: A simple conceptual relationship between MGNREGA and contraceptive use.



Note: The area within the dashed line represents the common support. The highest propensity score for untreated is 0.9636089 and the lowest propensity score for treated is 0.044275. Source: Own calculation

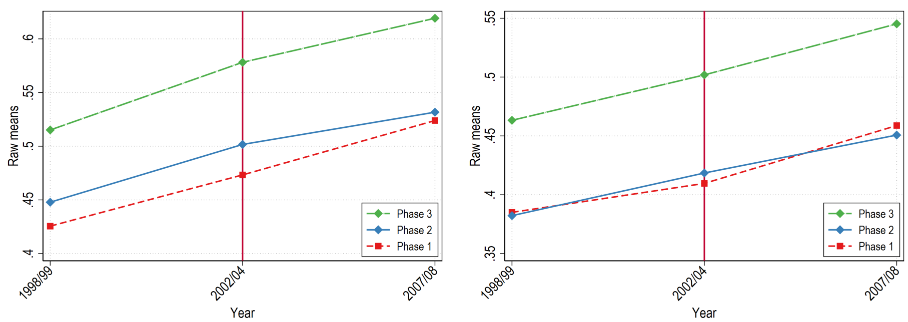
Figure 1.3: Propensity score distribution by treatment groups.



(a) Any methods **(b)** Any modern methods

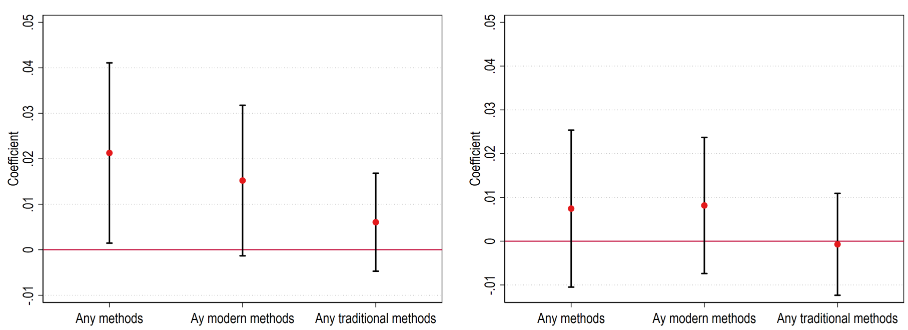
Note: The omitted category is DLHS-2 (Event Time = -1)

Figure 1.4: Event-study regression



(a) Any methods **(b)** Any modern methods

Figure 1.5: Pre-program trends across MGNREGA implementation phases.



(a) Phase 1 (2006) x $Post_{2008}$ **(b)** Phase 2 (2007) x $Post_{2008}$

Note: Figure in the left panel compare districts in phase 1 and phase 3, excluding phase 2. Right panel compares districts in phase 2 and phase 3, excluding phase 1.

Figure 1.6: Differential effects of MGNREGA.

Table 1.1: District Summary Statistics

	Pre-Program (2002-2004)		
	Treated	Control	Diff. (*p*-value)
Propensity score	0.540	0.580	0.412
	(0.309)	(0.264)	
Total Population (in thousands)	1685.455	1423.395	0.125
	(1374.647)	(1140.525)	
Percent rural	0.791	0.799	0.674
	(0.145)	(0.114)	
Area (in square km)	116.355	109.100	0.650
	(143.130)	(135.001)	
Percent Scheduled Castes	0.157	0.141	0.282
	(0.088)	(0.094)	
Percent Scheduled Tribes	0.143	0.218	0.209
	(0.223)	(0.344)	
Percent Literate	0.547	0.535	0.457
	(0.118)	(0.100)	
Average MPCE	3524.572	3466.498	0.704
	(1057.067)	(1076.334)	
Average casual wage	329.410	334.066	0.671
	(134.240)	(133.176)	
Labor force participation rate	0.657	0.669	0.493
	(0.089)	(0.105)	
Female labor force participation rate	0.201	0.220	0.225
	(0.095)	(0.106)	
Rainfall (mm)	1217.950	1404.769	0.268
	(712.139)	(1113.264)	
Growing degree days	2366.131	2251.824	0.207
	(462.101)	(603.619)	
Number of observations	152,370	104,455	571,080
Number of districts	282	198	480

Note: Standard deviations are in parentheses. Sample restricted to common support region. Treated includes phase one and two districts, and control includes phase three districts. The third column, difference, is calculated with WLS regressions and clustered standard errors at the district level. MPCE refers to the monthly per capita consumption expenditure. Average MPCE and casual wage are in 2004-2005 prices.

Table 1.2: Individual Summary Statistics

	Pre-Program (2002-2004)		
	Treated	Control	Diff. (*p*-value)
Outcomes			
Any family planning methods	0.551	0.517	0.282
	(0.497)	(0.499)	
	[152,370]	[104,455]	
Any modern methods	0.478	0.438	0.179
	(0.500)	(0.496)	
	[152,370]	[104,455]	
Any traditional methods	0.074	0.079	0.638
	(0.261)	(0.269)	
	[152,370]	[104,455]	
Among women who are currently taking contraceptives.			
Female sterilization	0.663	0.630	0.260
	(0.473)	(0.483)	
	[76,945]	[61,207]	
Male sterilization	0.022	0.018	0.365
	(0.147)	(0.133)	
	[76,945]	[61,207]	
Intrauterine Device (IUD)	0.033	0.044	0.128
	(0.180)	(0.204)	
	[76,945]	[61,207]	
Oral pills	0.071	0.081	0.446
	(0.256)	(0.273)	
	[76,945]	[61,207]	
Condom	0.072	0.073	0.928
	(0.258)	(0.260)	
	[76,945]	[61,207]	
Rhythm/Periodic abstinence/Withdrawal	0.122	0.144	0.234
	(0.327)	(0.351)	
	[76,945]	[61,207]	

Note: Standard deviations are in parentheses. Observations are in square bracket. Sample is restricted to common support region. Treated includes phase one and two districts, and control includes phase three districts. The third column, difference, is calculated with WLS regressions and clustered standard errors at the district level. Source: DLHS round 2 (2002-2004).

Table 1.3: Effect of MGNREGA on the use of family planning methods - Placebo

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post	-0.011	-0.012	0.001
	(0.011)	(0.008)	(0.007)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.484	0.422	0.062
SD dependent variable	0.500	0.494	0.241
Observations	549,059	549,059	549,059
Number of districts	422	422	422
R-squared	0.150	0.146	0.097

Note: Robust standard errors are in parentheses and clustered at the district level. The sample is restricted to common support. WLS estimator is used across all regressions. $Post$ is a dummy variable indicating that the observation is from the 2002/04 round. All dependent variables are binary (1/0). Any methods refer to individuals who are currently using any family planning methods. Modern methods include sterilization of women and men, IUDs/copper-t/loop, oral pills, male and female condoms, and others. Traditional methods include using rhythm, periodically abstinence, withdrawal, and others.

Table 1.4: Effect of MGNREGA on the use of family planning methods

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post	0.018**	0.014**	0.004
	(0.008)	(0.006)	(0.005)
Individual-level and household controls			
Women age in years	0.014***	0.014***	-0.0002*
	(0.0004)	(0.0004)	(0.0001)
Women can read or write	0.057***	0.043***	0.014***
	(0.005)	(0.004)	(0.001)
Spouse can read or write	0.056***	0.048***	0.008***
	(0.003)	(0.003)	(0.001)
Number of children	0.043***	0.038***	0.005***
	(0.003)	(0.003)	(0.001)
Religion: Hindu	0.094***	0.090***	0.004
	(0.012)	(0.012)	(0.003)
Scheduled castes/tribes	-0.042***	-0.039***	-0.003**
	(0.005)	(0.006)	(0.001)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.558	0.486	0.072
SD dependent variable	0.497	0.500	0.259
Observations	570,193	570,193	570,193
Number of districts	480	480	480
R-square	0.220	0.227	0.091

Note: Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). Sample is restricted to common support and excludes currently pregnant women. WLS estimator is used for all regression. All dependent variables are binary (1/0). Any methods refer to individuals who are currently using any family planning methods. Modern methods include sterilization of women and men, IUDs/copper-t/loop, oral pills, male and female condoms, and others. Traditional methods include using rhythm, periodically abstinence, withdrawal, and others.

Table 1.5: Effect of MGNREGA on selected use of modern contraceptives

	Permanent contraceptives	Reversible contraceptives
Panel A: Age 18 to 34 years		
MGNREGA x Post	0.003	0.005
	(0.004)	(0.005)
Mean dependent variable	0.301	0.122
SD dependent variable	0.459	0.327
Observations	380,575	380,575
Number of districts	480	480
R-square	0.293	0.112
Panel B: Age 35 years and older		
MGNREGA x Post	0.010	0.010**
	(0.007)	(0.004)
Mean dependent variable	0.533	0.066
SD dependent variable	0.499	0.248
Observations	189,616	189,616
Number of districts	480	480
R-squared	0.243	0.084
District FEs	Yes	Yes
State-year FEs	Yes	Yes
Interview month-year FEs	Yes	Yes

Note: Levels of significance: p$< 0.01^{***}$, p$< 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is restricted to common support and excludes current pregnant women. WLS estimator is used for all regressions. All dependent variables are binary (1/0). Controls at the individual and household level are included in every regression. The minimum age for working in the MGNREGA is 18. Permanent contraceptives include female and male sterilization. Reversible contraceptives include IUDs/Copper-t/Loop, oral pills, male and female condoms, and others.

Table 1.6: Effect of MGNREGA on woman's age at first birth

	Woman's age at first birth
MGNREGA x Post	0.110**
	(0.051)
District FEs	Yes
State-year FEs	Yes
Interview month-year FEs	Yes
Mean dependent variable	19.361
SD dependent variable	3.239
Observations	525,573
Number of districts	480
R-squared	0.180

Note: Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is restricted to common support and excludes current pregnant women. WLS estimator is used for all regressions. All dependent variables are binary (1/0). Controls at the individual and household level are included in every regression.

Table 1.7: Differential impacts of MGNREGA on the use of family planning in the Phase 1 and in the Phase 2 districts

	Any methods	Any modern methods	Any traditional methods
Phase 1 x Post	0.037***	0.029***	0.008
	(0.009)	(0.007)	(0.005)
Phase 2 x Post	0.008	0.010	-0.002
	(0.010)	(0.008)	(0.007)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.554	0.481	0.073
SD dependent variable	0.497	0.500	0.260
Observations	630,173	630,173	630,173
Number of districts	536	536	536
R-square	0.218	0.227	0.090
p-val[Phase 1 x Post = Phase 2 x Post]	0.285	0.277	0.718

Note: Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). Individual- and household-level controls are included in all regressions. The row 'p-val[Phase 1 x Post = Phase 2 x Post]' reports the p-value of the test of difference in the coefficient across the interaction terms between Phase 1 and Post and Phase 2 and Post.

Table 1.8: Effect of MGNREGA on the use of family planning methods by star states: Triple difference

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post x Star states	0.0004	0.007	-0.006
	(0.016)	(0.015)	(0.009)
MGNREGA x Post	0.018*	0.012*	0.006
	(0.009)	(0.007)	(0.008)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.558	0.486	0.072
SD dependent variable	0.497	0.500	0.259
Observations	570,193	570,193	570,193
Number of districts	480	480	480
R-squared	0.220	0.227	0.091

Note: Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is restricted to common support and excludes current pregnant women. WLS estimator is used across all regressions. All regressions include controls at the individual and household level. Star states include Andhra Pradesh, Himachal Pradesh, Madhya Pradesh, Chattisgarh, Rajasthan, Uttarakhand and Tamil Nadu. Imbert and Papp [2015]. See note to Table 1.4 for other details.

Table 1.9: Effect of MGNREGA on the use of family planning methods

	Any methods	Any modern methods	Any traditional methods
Panel A: Low wealth index			
MGNREGA x Post	0.027**	0.017*	0.011
	(0.012)	(0.009)	(0.008)
Mean dependent variable	0.468	0.397	0.071
SD dependent variable	0.499	0.489	0.257
Observations	272,016	272,016	272,016
Number of districts	480	480	480
R-square	0.225	0.237	0.109
Panel B: Medium wealth index			
MGNREGA x Post	0.008	0.006	0.002
	(0.008)	(0.007)	(0.005)
Mean dependent variable	0.610	0.541	0.069
SD dependent variable	0.488	0.498	0.253
Observations	198,917	198,917	198,917
Number of districts	480	480	480
R-squared	0.210	0.220	0.092
Panel C: High wealth index			
MGNREGA x Post	0.021**	0.028***	-0.008
	(0.008)	(0.009)	(0.007)
Mean dependent variable	0.668	0.587	0.082
SD dependent variable	0.471	0.492	0.274
Observations	99,183	99,183	99,183
Number of districts	479	479	479
R-squared	0.176	0.180	0.076

Note: Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is restricted to common support and excludes current pregnant women. WLS estimator is used across all regressions. All regressions include controls at the individual and household level. District, state-year, and interview month-year fixed effects are included in all regressions.

Chapter 2

Rainfall shocks, soil health, and child health outcomes

2.1 Introduction

India consistently ranks low on the global hunger index, according to four indicators: malnutrition prevalence, child wasting (a measure of short-term inadequate nutrition), child stunting (a measure of long-term inadequate nutrition), and under-five mortality [Wiesmann, 2006]. Many of India's villages in 2016 showed alarming levels of anthropometric measurements in children [Kim et al., 2021]. According to the 2015-2016 India Demographic and Health Survey, 38% of children under the age of 5 are stunted (too short for their age) and 21% of children under the age of 5 are wasted (too thin for their height). Indian agricultural production is vulnerable to climate change and, without effective adaptation, can reduce food crop yields in the future by up to 9% [Guiteras, 2009]. Moreover, in India's recent past, shortages of staple food crops, wheat and rice are associated with severe droughts and extreme rainfall [Zaveri and B Lobell, 2019, Auffhammer et al., 2012]. Child nutrition and agricultural production in rural areas in the developing world are closely linked [Webb and Block, 2012]. Bakhtsiyarava and Grace [2021] in Ethiopia demonstrated that more diversity in agricultural production during periods of low rainfall can reduce the risk of chronic food insecurity among children. Food shortages caused by crop failures due to extreme weather conditions, and the resulting nutritional deprivation can negatively impact children's health [Grace et al., 2012]. Improved soil quality as measured by soil organic carbon (SOC), commonly used in the literature, increases agricultural production [Lal, 2006]. Because of the water holding capacity, a high level of SOC offers long-term drought resistance and reduces the frequency of crop failures [Huang et al., 2021, Kane et al., 2021]. SOC also provides agricultural profits for small landowners in developing countries [Bhargava et al., 2018]. My research asks if SOC affects children's nutrition and health in a low-income country. Then, I explore to what extent SOC offers resilience during periods of low rainfall.

This article examines whether natural variation in soil organic carbon levels mitigates the impact of non-linear weather variables by crop growth on children's health. Focusing on rural India, I leverage the 2015 Demographic and Health Survey dataset and high-resolution spatial data on soil organic carbon content and meteorological variables. Following Bakhtsiyarava and Grace [2021], I evaluate the variation in anthropometric measurements, height-for-age (HAZ) and weight-for-height z-scores (WHZ) to measure child malnutrition in India. Inadequate nutrition can cause childhood stunting (if HAZ is below 2 standard deviation) and wasting (if WHZ is below 2 standard deviation). Unlike stunting, wasting may be reversed by increasing nutritional intake [Victora, 1992]. In this study, I focus on HAZ and WHZ to measure malnutrition linked to weather-induced food insecurity.

While the exact relationship between soil quality and crop production under dry conditions is complex and multidimensional. Huang et al. [2021] and Kane et al. [2021] in the United States show that a higher soil organic carbon content can moderate the impact of weather shocks by retaining soil water in the agricultural systems. Children's nutrition also depends on food quality, which is partly dependent on soil micro-nutrients [Berkhout et al., 2019, Kim and Bevis, 2019]. Berkhout et al. [2019], based on their study in Sub-Saharan Africa, highlight the importance of soil micro-nutrients such as zinc, copper and manganese in reducing the malnutrition in children.

This article is informed and contributes to two main strands of the literature: the first is the relationship between soil agronomy and climate; the second is the relationship between children's health and SOC. While there are studies that examine the impact of climate on children's health in India (e.g., Dimitrova and Muttarak [2020] and McMahon and Gray [2021]), these studies have overlooked the importance of soil health. In this article, I contribute to the literature by demonstrating the direct and indirect effects of SOC. By enhancing the SOC, households would have access to greater food availability that could support children's nutrition and health. This is a direct result of

SOC. The SOC may also help mitigate the impact of adverse weather conditions on food quantity. This is an indirect effect of SOC.

I find that higher soil organic carbon levels attenuate about 3% of the negative effect of rainfall shock on children's weight-for-height z-scores. I show that a small change in soil health can offer resistance to wasting in children during periods of low rainfall. I also explore heterogeneity in children's health outcomes by gender, household wealth index and land ownership, and climate zone. This suggests that efforts to improve soil quality should be adjusted to address these heterogeneous impacts. The results of the paper provide new evidence and inform policy-makers on the impact of high organic carbon in soils on children's health.

2.2 Conceptual Framework

Figure 2.1 depicts a simple conceptual connection between soil health and childhood nutrition. The figure can be used to examine the impact of a rainfall shock with different levels of SOC. Because periods of low precipitation reduce crop yields, food shortages affect food intake and thus nutrition [Grace et al., 2012]. Higher SOC levels increase in agricultural production, particularly during a drought [Lal, 2006], which contributes to food availability and supports nutrition through consumption of output and income from crop sales that can be used to purchase food. Because of the water holding capacity, a high level of SOC offers long-term drought resistance and reduces the frequency of crop failures [Huang et al., 2021, Kane et al., 2021]. This reduction in crop failure increases agricultural income overall [Bhargava et al., 2018] and can thus contribute to food security and nutrition for children by providing an extra cushion against shocks.

Furthermore, the level of education of the mother, the gender of the child and the wealth of the household can also influence the nutrition of the children [Almond and Currie, 2011]. Moreover, SOC mitigation effects may vary depending on climate regions and the ability of households to cope with rain shocks. Later in the results section, I estimate the heterogeneity in children's health outcomes by region, climate zone, gender, household wealth and land ownership. Also, there may be unobserved covariates which may be correlated with children's nutrition and soil organic carbon levels and therefore may bias my results downwards.

2.3 Data and Descriptive statistics

To demonstrate how soil organic carbon levels moderate the effect of monsoon activity on the health of Indian children, I leverage the Demographic and Health Survey dataset and high-resolution spatial data on soil organic carbon levels and weather variables.

2.3.1 Demographic and Health Data

I use the cross-sectional data from the fourth round of the Demographic and Health Survey (DHS) for India collected in 2015-2016. DHS uses a multi-stage stratified sampling design, with enumeration areas, hereinafter referred to as clusters (equivalent to census villages), being the smallest unit. In the clusters, households are randomly selected to be interviewed. DHS also collects the GPS locations of each cluster, enabling researchers to link DHS dataset to other geo-coded data, including soil organic carbon levels, precipitation, and temperature, at the cluster level. In order to preserve the anonymity of the villages, DHS randomly displaces the GPS coordinates of clusters up to 2 Km in urban areas and up to 5 Km in rural areas, and 1% of rural clusters are further displaced up to 10 Km. This displacement introduces measurement errors and may bias my results downwards.

131 of the 28,526 geo-referenced clusters did not have information and were dropped. I extracted environmental data using the DHS geo-referenced cluster for a 10-km buffer.[19]

DHS has a nationwide representative sample of children. In my analysis, the sample size for children aged 0 to 4 years was 259,627; 34,625 observations were excluded from the child data file that contained missing or invalid data. Invalid cases include children over plausible limits, age over plausible limits, and flagged cases. Additionally, observations with invalid woman's Body Mass Index (BMI) information (636 observations), missing data (6,447 observation) on caste, and not

[19] As a sensitivity test, I run every analysis for a 20-km buffer. Appendix Table A.20 reports the main results.

useful information (929 observations had “don’t know" on caste) were excluded. Furthermore, I restrict the sample to focus exclusively on rural parts of the country as defined in the DHS dataset. To sum up, I analyzed a sample of 169,904 rural Indian children.

2.3.2 Rainfall Data

I draw monthly rainfall data from Climate Hazards Group Infrared Precipitation (CHIRPS) using DHS cluster geocordinates. CHIRPS is a quasi-global that extends over 50 S-50 N, with a gridded resolution of 0.05 degrees, from 1981 to near-real time precipitation time series [Funk et al., 2014].

There is not much guidance available in the literature about defining rain shock. For my purpose, I need to define a rainfall shock based on a threshold that lowers yields on India’s major crops. Therefore, like Feeny et al. [2021a], I adopt an empirical strategy to determine the threshold. Using data from the International Crops Research Institute for the Semi-Arid Tropic (ICRISAT), I regress the natural log of the annual crop yield (Kg per hectare) from 2001 to 2015 on rainfall deciles controlling for year and district fixed effects.[20] The unit of analysis for the yield data is the district-year. As shown in the Figure 2.2, results indicate that rainfall below the 20th percentile reduces crop yield of grains and pulses in India.[21] Additionally, I also check the moderating effects of high SOC on crop yields. I interact with rainfall deciles and high SOC levels. The absolute impact of a high level of SOC is not statistically significant. However, the terms of interaction between precipitation deciles and high SOC are statistically significant for rainfall deciles 1 and 7. The results suggest that SOC moderated the impact of fluctuations in precipitation on yields in my analysis. Appendix Table A.23 report the results.

[20] Crop yield data (unapportioned) are available at http://data.icrisat.org/dld/index.html

[21] In the appendix, Figure A1, I also show the negative effects of lower precipitation on selected staple and cash crops. Corn, soybeans and cotton appear to differ and not increase monotonously with precipitation, suggesting a non-linear response to weather conditions in some field crops.

I define rain shock as a monsoon rain that is below the 20th percentile of the long-term historical mean within the DHS cluster [Shah and Steinberg, 2017].[22]

I used a measure of rainfall shock, which has already been used in the literature [Feeny et al., 2021a, Dinkelman, 2017]. Following Dinkelman [2017], I calculate the fraction of shocks:

$$\text{Fraction shocks}_{ij} = \frac{[\text{child's exposure to shocks in-utero through age 4}]_{ij}}{(\text{in-utero + child's age})_{ij}}.$$

where the subscripts i represent every child in the sample living in clusters j. By using the shock fraction, I capture the variation in the rain shock specific to the child living in the clusters.

A child under the age of 5 years may be exposed to one, many or no monsoon rainfall shock; the fraction of shocks captures that intensity of shock. For example, if a child of age 3 was exposed twice to rainfall shocks over his or her lifetime then the fraction of shocks for that child is given by $2/4$. To measure the *in-utero* exposure to rainfall shock, I used the birthyear of the individuals observed in the DHS data.

To serve as a robustness check, I construct a population-weighted monthly rain measure based on gridded population data provided by the Center for International Earth Science Information Network [Center for International Earth Science Information Network - CIESIN - Columbia University, 2018].[23]

2.3.3 Growing Degree Days

Daily temperature was sourced from Indian Monsoon Data Assimilation and Analysis (IMDAA) reanalysis portal, managed by the National Centre for Medium Range Weather Forecasting (NCMRWF), India [Rani et al., 2021]. Reanalysis Data Service (RDS) is a regional atmospheric reanalysis over the Indian subcontinent at a high resolution 0.12 x 0.12 from 1979-2018.[24] I have

[22] India receives the majority of its rainfall during the monsoon from June to September.

[23] For my analysis, I use a resolution of 2.5 arc-minute for the year 2015. Data is available at https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-rev11/data-download

[24] Available at https://rds.ncmrwf.gov.in/datasets

followed the formulation used in previous studies using meteorological measures which affect crop losses [Guiteras, 2009].[25] Using the maximum and minimum daily temperature, the lower and upper threshold for calculating Growing Degree Days (GDD) during a growing season were set to $8C$ and $32C$, respectively.

2.3.4 Soil Data

Soil organic carbon data were obtained from OpenLandMap [Hengl and Wheeler, 2018].[26] Global soil maps were produced based on machine learning predictions from global soil profile compilations at a resolution of 250 m. Following Huang et al. [2021], I extracted the mean soil organic carbon content around the DHS geo-coded clusters at four standard depths: 0, 10, 30, and 60 cm. I then calculated the depth-weighted soil organic carbon content at 0-60cm interval for the analysis.[27] The literature does not provide clear information about the threshold for classifying soil as high or low quality. Therefore, I have identified two categories of soil organic carbon content: low, below the 50th percentile, and high, above the 50th percentile.[28]

Figure 3.1 shows the soil organic carbon map for the rural DHS clusters. The missing area in the map indicates the null values for union territory Lakshadweep. Much of India is categorized as having low levels of soil organic carbon. The average soil organic carbon concentration is 0.945 %(g/Kg). Coastal regions in the west and east, most in the northeast and central plains

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[25] Following Guiteras [2009], I convert the daily mean temperature to GDD:

$$GDD(T)_j = \begin{cases} 0, & \text{if } T \leq 8C \\ T-8, & \text{if } 8C < T \leq 32C \\ 24, & \text{if } T \geq 32C \end{cases}$$

[26] Soil data are available at https://www.openlandmap.org

[27] Following Huang et al. [2021], I used the trapezoidal rule to estimate the depth-weighted 0-60cm interval:

$$(S_{0-60cm})_j = \left(\frac{[(S_0 + S_{10}) * 10 * 0.5] + [(S_{10} + S_{30}) * 20 * 0.5] + [(S_{30} + S_{60}) * 30 * 0.5]}{60} \right)_j$$

[28] I also perform the sensitivity test for different threshold values such as 25th and 75th percentile of high soil organic carbon. Appendix table A.18 and A.19 report the results.

are characterized by moderate to high soil carbon levels. Also, to explore what determines SOC variation, I do the Pearson correlation coefficient test between soil organic carbon and the historical enhanced vegetation index.[29] The Pearson coefficient of correlation between these two variables is 0.38 (p-val = 0.000).

2.3.5 Descriptive statistics

Anthropometric data or body measurements for children, such as weight-for-age and weight-for-height, are taken and compared to a table in the World Health Organization (WHO) Child Growth Standards to calculate z-scores [WHO, 2006]. The WHO Child Growth Standards are based on a sample of children from six countries: Brazil, Ghana, India, Norway, Oman and the United States of America. The z-score value can be either negative or positive depending on whether a child's anthropometric measurement is below or above the population average for the child's age and sex. The children in the sample have a negative value of z scores, suggesting infants with low birth weight, on average. The distribution of each anthropometric measure within the sample differs for boys and girls. Among boys, the height-for-age is -1.597, the weight-for-age z is -1.602 and the weight-for-height is -1.017. In girls, the height-for-age z score is -1.516, the weight-for-age is -1.572, and the weight-for-height is -0.963.

Figures 2.4a and 2.4b show the distribution of height-for-age (HAZ) and weight-for-height (WHZ) z scores of children under 5 years of age. The shaded portion in the figure shows the frequency indicating the absolute magnitude of child stunting and wasting. In my sample, approximately 41 per cent of children are stunted and approximately 21 per cent of children are wasted.

Table 2.1 reports the summary statistics for the data used in this study.About 11 percent of children were exposed to at least one rainfall shock in their birth year and in-utero. Children aged 2 to 4 are more exposed to cumulative shocks ranging from 0.15 to 0.17. This means that children aged 2 to 4 may have been exposed to at least one rainfall shock in their lifetime. The average value of the fraction of shocks as an intensity measure is 0.13.

[29] I observe the enhanced vegetation index in the DHS dataset from 1985 to 2015 at 5-year intervals.

In my sample, the average age of children is 30 months. 51 per cent are boys and 49 per cent are girls. On average, mothers are 27 years of age and approximately half of the women have a high school or higher education. A little over half the households have agricultural land. Just under a third of households have potable water lines and a third have flush toilets. 23 per cent of families in my sample are poor.

2.4 Empirical Framework

I estimate an OLS regression model to investigate the impact of high soil organic carbon levels on children's nutrition and health. mitigate the negative impact of shocks on children's health. The main specification is given by

$$h_{ij} = \beta_1 shock_{ij} + \beta_2 soc_j + \beta_3(shock_{ij} * soc_j) + f(\theta)_{ij} + \xi \mathbf{X}_i + f(a)_i + \delta_d + \phi_{my} + \varepsilon_{ij} \quad (2.1)$$

where h_{ij} denotes child health outcomes measured by the height-for-age, weight-for-age, and the weight-for-height z-scores for child i at the DHS cluster level, j; $shock_{ij}$ represents the fraction of rain shocks experience by child i residing at DHS cluster level, j; soc_j represents the mean soil organic carbon content at the DHS cluster level, j; $\mathbf{X}_i$ is a set of explanatory variables including child, mother, and household characteristics. Child characteristics include age, gender and order of birth; mother characteristics include age, level of education and diet; and household characteristics include religion, social group, household income, and the wealth index δ_d denotes district fixed effects and captures the time-invariant unobserved heterogeneity at the district level; ϕ_{my} denotes child birth year-month specific fixed effects and captures within cohort variations, and ε_{ij} denotes the disturbance terms. I cluster the standard errors at the level of DHS cluster (equivalent to Census village).

Additionally, I control precipitation and temperature derivatives (growth degree-days and harmful degree-days) during a growing season (June through September) throughout a child's life. $f(\theta)_{ij}$ is a non-linear function of precipitation and temperature. I followed [Dimitrova and Muttarak, 2020] to include a restricted cubic age spline, $f(a)_i$ with knots 6, 12, 18, 24, 36, and 48 months of age to control for non-linearity in children's growth trajectory. The key parameters are β_1, β_2, and β_3. β_1 represents the impact of cumulative periods of low precipitation on children's health; β_2 represents the direct impact of a high level of SOC on children's health; and β_3 represents the mitigation effects of a high level of SOC during cumulative periods of low rainfall.

In this study, I assume the soil endowments are exogenous. Because any change in agriculture, including climate change, takes a long time to get reflected in the soil system [Lal, 2004]. This can mean that investment in soil or soil degradation by intensive cropping may take a long time to be reflected in the soil system. Also, because of India's low weather-induced internal migration rate [Viswanathan and Kumar, 2015]. Because in my analysis, I look at short-term weather conditions on children's nutrition and health. That is a plausible assumption.

There may be a potential threat to identification. Some regions may experience larger declines in soil organic carbon content than others, resulting in measurement errors. For example, in wheat fields, stubble burning is often done after harvest, which can disrupt the natural cycle of soil organic carbon replenishment. However, because of the invariant time measure of the soil, I am unable to capture this variation.

Nevertheless, I take advantage of the coarsened exact matching method to estimate causal effects by reducing the covariate imbalance between treatment and control groups [Iacus et al., 2012]. However, it may not circumvent the sample selection problem.

2.4.1 Matching methods

The coarsened exact matching method estimates the average effect of treatment on the treated sample [Blackwell et al., 2009]. I use data knowledge to search for a better match. The coarsened variables used were: a) child-specific (child's birth order, child's gender and age); b) mother-specific (mother's age and education level); and c) household-specific (religion, caste, source of drinking water, and toilet facility).[30] I apply the software package, *cem* created by [Blackwell

[30]I also included the month of birth as part of the matching algorithm. I calculated if a child was born during the dry season (the first six months of the year) or the wet season (the last six months of the year). Then I included that as

et al., 2009] was used to calculate the weights and these weights were used in a simple weighted regression.[31] The treatment variable treat, is 1 for high soil organic carbon content (in treatment group) and 0 for low soil organic carbon content (control group). Here is the summary of the match: the number of balanced matched observations is 51,148 for treatment and control; and the unmatched observation is 33,802 out of 84,950 for control and 33,806 out of 84,954 for treatment.

2.5 Results

2.5.1 Rainfall shocks, soil health, and child health

Table 2.2 presents impact of rainfall shock and soil health on children's health. The OLS model takes into account the characteristics of the child, the mother, the household. Moreover, the model controls a child's lifetime exposure to rain and temperature during a growing season. The model includes district and month and year of birth fixed effects. Standard errors are clustered at the DHS cluster level. The shock fraction shows a significant negative association with child WHZ. A one standard deviation increase in rainfall shock exposure above the child average years of exposure implies that the child will have 0.029 (0.161*0.182 = 0.029)[32] lower weight-for-height z score. A high level of SOC has no effect on children's health at its main term, but substantially reduces the negative effect of the precipitation shock by 13.6 percentage points.

The interaction term between SOC and fraction of shocks, which captures the compensating effect of a high soil quality. The coefficient on the interaction term is 0.136 and significant at the 5% significance level suggesting that a higher soil organic carbon content moderates approximately 3% $\left(\frac{-0.161+0.136}{-0.991} = 0.025\right)$[33] of the negative effect of monsoon rainfall on child weight-for-height z score.

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an additional variable in the matching algorithm. Appendix Table A.21 presents the results. It reads findings similar to those of the main specification.

[31]The *cem* command with a *k2k* option in STATA produces a match result which has the same number of treated and control in each matched strata by dropping the observations randomly.

[32]The standard deviation for the shock fraction variable is 0.182.

[33]The mean dependent variable is -0.991.

Columns 3 and 4 in Table 2.2 present the results after applying the coarsened exact matching weights to the OLS model. The shock fraction is negatively related to the child's WHZ. The interaction term between SOC and fraction of shocks shows a positive association. However, the key coefficients are not significant at the 5 per cent significance level in the matched sample. In addition, I find no significant association between SOC and the child's HAZ for the full and matched sample. Appendix Table A.15, which uses the population-weighted monthly rain measures, reads similar effects on child health.

Figures 2.5a and 2.5b illustrates the average marginal effects of high soil organic carbon on anthropometric measures in children. The figure suggests that a high level of SOC reduces the negative impact of rain shocks on children's WHZ. The attenuation effect of high SOC levels during periods of low precipitation is greater for high shock intensity. Graph a in Figure 5 shows an interesting result: the child's height-for-age z score shows an upward slope suggesting that the cumulative period of dryness improved the height-for-age z scores. However, at high shock intensity, the average marginal effect is statistically insignificant (as shown in graph c). This may be due to a reduction in diseases that are common during monsoons such as diarrhoea and malaria. But it requires further research and the results have to be interpreted with caution.

There is a concern that soil organic carbon measurement may be confounded by other associated agronomic attributes. With SOC as the choice variable, it is difficult to remove concerns related to the omitted variable bias. Nevertheless, I approach this concern by including soil texture, slope and vegetative index as control variables in Equation 2.1.[34,35] In order to assess the influence of the different soil attributes used in this study on children's health, I ran a correlation between child WHZ and soil attributes. This demonstrates no concern for multicollinearity in the model. Table A.16 in the appendix provides the correlation matrix for the soil attributes used in this study. Appendix Table A.17 report the results. It reads similar effects on child health.

[34] I used OpenLandMap to extract clay, sand, and silt content in $\%(kg/kg)$ at a depth of 60cm in the DHS cluster [Hengl, 2018a,b,c].

[35] I used the enhanced vegetation index for 2015 available in the DHS dataset as a proxy for agricultural output.

2.5.2 Heterogeneity

Heterogeneity by climate zone

The impact of soil organic carbon on children's health can vary according to climate zones in India. Following Dimitrova and Bora [2020], I constructed six major climate zones at the district level based on the basis of the climate classification Köppen Geiger.[36] They are tropical wet, tropical wet and dry, arid, semi-arid, humid sub-tropical, and mountainous. See Appendix A.5 for a map of the main climatic zones in India.

Table 2.3 presents the heterogeneous effects of a high level of SOC on children's health in some climatic zones. Each column of Table 2.3 presents the regression results for the separate climatic zones. Cumulative rain shocks have a negative impact on the health of children living in semi-arid and humid sub-tropical climate zones. The impact is greater in semi-arid climate zones. Point estimate is -0.280 and significant at the 5% significance level. The interaction term of the shock fraction with SOC is positive and significant at the 5% significance level, suggesting mitigating effects of a high level of SOC. The shock fraction positively affects the WHZ of children in tropical wet and dry and a high level of SOC decreases WHZ during the cumulative periods of low rainfall.

The results suggest no impact of a high level of SOC on the child's HAZ in any major but semi-arid climatic zones. Furthermore, a high level of SOC lowers the child's HAZ during periods of low rainfall.

Heterogeneity by gender

Table 2.4 presents the heterogeneous effects of rainfall shocks and soil health on children's health by gender. Each column in Table 2.4 shows the separate regression results for boys and girls. Cumulative rain shock has a negative impact on girls' and boys' WHZ scores. Girls are more affected by rain shocks, as suggested by the larger coefficient. The point estimation is -0.205 for girls and -0.112 for boys. A high level of SOC positively impacts WHZ scores for girls during

[36] I am grateful to Anna Dimitrova for sharing the data and code with me.

cumulative periods of low rainfall. The p-value of the test of the difference in the coefficient across girls and boys for the interaction terms between high SOC and fraction of shocks is not statistically different from zero. In addition, the results show that a high level of SOC does not affect the HAZ scores for boys and girls.

Heterogeneity by household wealth index

I observe five different indices of wealth in the DHS data: the poorest, the poorer, the middle, the richer, and the richest. For my purpose, I code the poorest and the poorer as the poor and the middle, the richer, and the richest as the non-poor.

Table 2.4 presents the heterogeneous effects of rainfall shocks and soil health on children's health by household wealth index, as defined in the DHS data. Each column in Table 2.4 presents separate regression results for children from poor and non-poor households. The results suggest that low-income households are negatively affected by rain shocks. The point estimate is -0.197 and significant at the 5% significance level. A high level of SOC does not reduce the negative effect of the rainfall shock on poor households. In addition, the cumulative rainfall shock and a high level of SOC have no impact on children's HAZ.

Heterogeneity by land ownership

Agriculture is the main occupation in rural India. To see if the results are determined by farm households, I examine the heterogeneity by land ownership: has farmland and has no farmland.

Table 2.4 presents the results for households that own and do not own farmland. The results suggest that rain shocks negatively affect households that own land, suggesting they are rain-dependent. A high level of SOC does not reduce the negative impact of rainfall shock on households that own land. Moreover, the cumulative rainfall shock and a high level of SOC have no impact on children's HAZ. In addition, the p-value difference test suggests that those who have agricultural land do not differ statistically from those who do not.

2.5.3 Extended results

Impact of SOC on childhood stunting and wasting

I estimate the logistic regression model to predict whether a switch from low to high SOC reduces the probability of stunting or wasting in children in response to rain shocks. Table 2.5 presents the effect of rain shocks on the probability of stunting and wasting in children and estimates the moderating effects of SOC. The dependent variable is binary for stunted children whose height-for-age is less than -2 $(HAZ < -2)$ is 1; 0 otherwise. Similarly, the binary for childhood wasting cases where the weight for height is less than -2 $(WHZ < -2)$ is 1; 0 otherwise. Results suggest that children exposed to cumulative rain shocks (in-utero to 4 years of age) are more likely to be wasted and less likely to be stunted.

Columns 1 and 2 in Table 2.5 show the results for the logit regression. Odd ratios of coefficients are provided. The odds of child wasting increased by 31$\%$ (1.309-1 = 0.309) in periods of low rainfall. Whereas, the odds of stunting in children is reduced by 13$\%$ (0.870-1 = -0.13) during periods of low rainfall. The odds of wasting for children living in high-level SOC areas is 5$\%$ (1.053-1=0.05) higher than in low-level SOC areas. That is a surprising result. To check for sensitivity to SOC threshold. I run the logit regression for different SOC thresholds. Appendix Table A.22 presents the results for the SOC threshold set at 25th, 50th, and 75th. We observe the mitigating effect of SOC during periods of low rainfall on childhood wasting at a threshold just above the 25th percentile and just above the 75th percentile. This means that a modest change in soil health may also improve children's health. The results suggest sensitivity to the SOC level. Therefore, my results must be interpreted cautiously.

The average marginal effects of the shock fraction at a low SOC level is 0.041 and significant at 1$\%$ significance level for children with wasting. Whereas, the average marginal effect of the shock fraction at a high SOC level is statistically not different from zero. Average marginal effects suggest that the probability of wasting in children living in low SOC areas increases by 0.04 percentage points during periods of low rainfall. The switch to high SOC levels attenuates this negative effect of cumulative rain shocks. The left and right graphs in Figure 6 show the average marginal effects on the probability of stunting and wasting in children.

Moreover, the results suggest that during periods of low rainfall, children are less likely to be stunted by 0.02 percentage points in regions with high or low SOC. This is reflected in the average negative marginal effects of stunting. It is noteworthy that cases of child stunting are chronic and difficult to explain simply by the agricultural process, including precipitation and soil quality. Furthermore, the results do not suggest any impact of a high level of SOC on stunting and wasting of children in the matched sample.

2.6 Conclusion

2.6.1 Summary

This article examines the relation between SOC and the impact of precipitation on children's health. The results demonstrate that a high level of SOC reduces the negative impact of rain shock on children's health in rural areas. Specifically, SOC affects the child's WHZ but has no effect on the HAZ. I find that SOC has a significant moderating effect on girls, but not on boys. Moreover, a high level of SOC ensures resilience in semi-arid and humid tropical climatic zones.

I find that the high level of SOC makes children resilient to wasting during periods of low rainfall. I also find that the shock fraction reduces the likelihood of child stunting, a long-term measure of health, and requires additional research. Results suggest a sensitivity to SOC threshold levels. Note that the regression results for the matched sample are sensitive to the variables used in the matching algorithm and the SOC threshold as treatment. Therefore, my results need to be interpreted cautiously.

2.6.2 Limitation

One limitation is that the soil organic carbon content variable used in this analysis is time invariant. Existing research shows that agricultural practices that cause pollution, such as stubble burning [Singh et al., 2019] and fertilizer use [Brainerd and Menon, 2014], can have negative impacts on children's health. Such agricultural practices may also have an impact on the concentrations of organic carbon in the soil. Therefore, estimates may be subject to upward bias because of the omitted variable. Due to a lack of data, I am unable to control for these practices. Nevertheless, it is important to explore these pathways in future research efforts.

2.6.3 Conclusions

Since it takes longer to reflect changes in soil organic carbon concentrations, policies may include both long-term and short-term measures. One long-term policy to enhance SOC would be to incentivize the adoption of agricultural best management practices. This can increase resilience to shocks over time, particularly as climate changes. Child development programs in India could be improved by considering the impact of climate change on the frequency of drought shocks and therefore on children's health.

In the short term, the soil health in a region could be used for information on the likely impacts of drought shocks, potentially allowing for better targeting of relief efforts. Food nutrients and soil conditions are interlinked through agriculture, and better soil quality helps reduce malnutrition during drought shocks. Therefore, scarce food relief may be more needed in areas of low SOC.

2.6.4 Future work

Breastfeeding provide nutrition to children in response to food insecurity and women's ability to breastfeed can be affected by environmental shocks. By linking soil quality to breastfeeding practices, we could better understand how children's nutrition responds to shocks.

Weather fluctuations impact the time- and gender-dependent nature of agricultural activities [Mahajan, 2017, Afridi et al., 2022]. For example, [Afridi et al., 2022] demonstrated that workdays on farm for Indian women were considerably shorter than those of men during a drought. Additionally, Mahajan [2017] show that rain-induced agricultural shocks affect women's wages differently than men's. Women's employment opportunities are closely related to children's nutrition [Debela et al., 2021]. There may be a direct negative impact on child nutrition if women have fewer employment opportunities. The SOC mitigation effect of the rain shock could increase women's resilience to employment opportunities in rural areas. That may be the subject of further research.

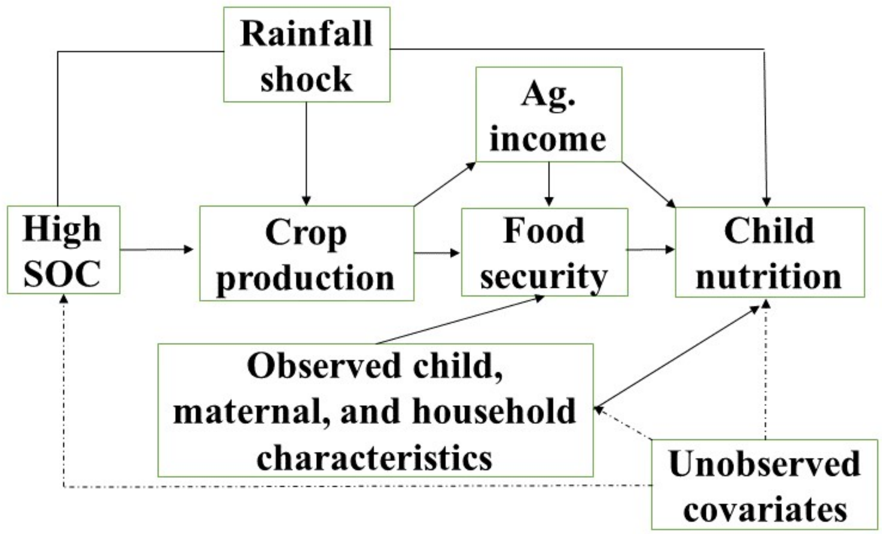
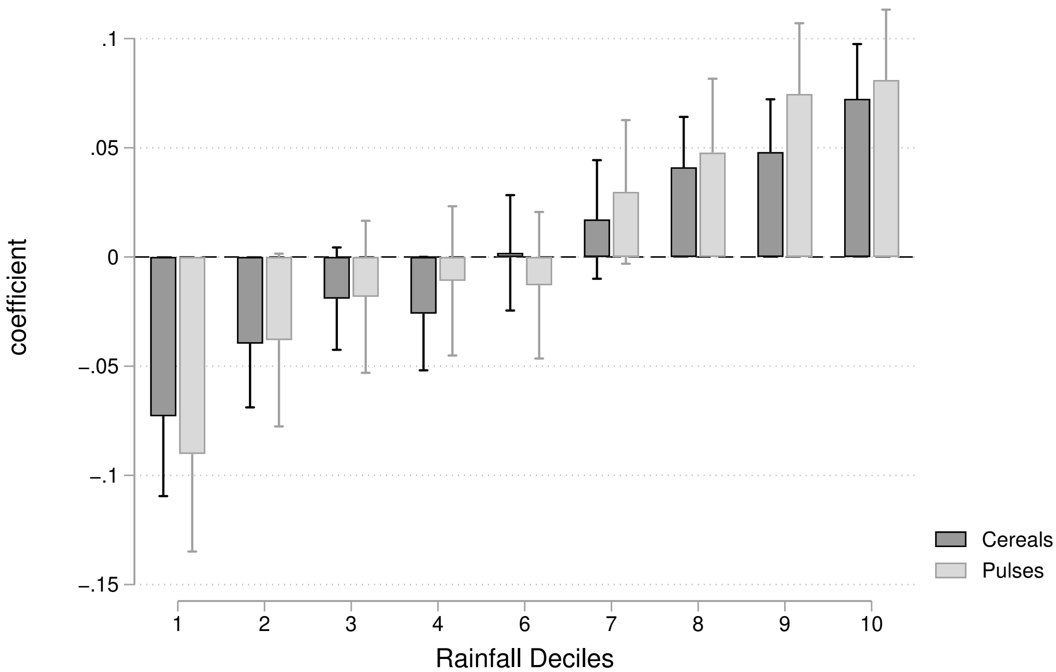
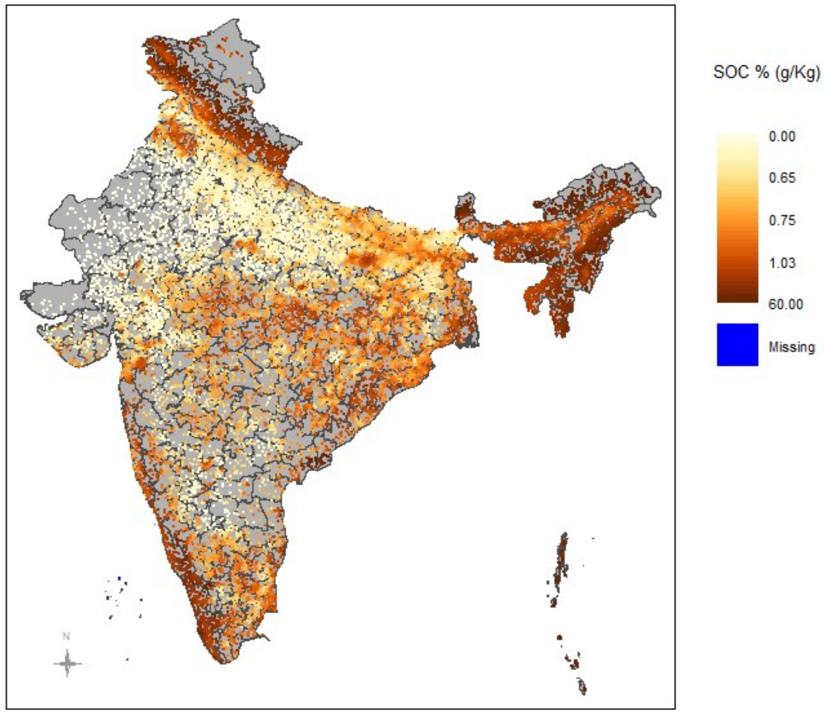


Figure 2.1: A simple conceptual relationship between soil and children's health.



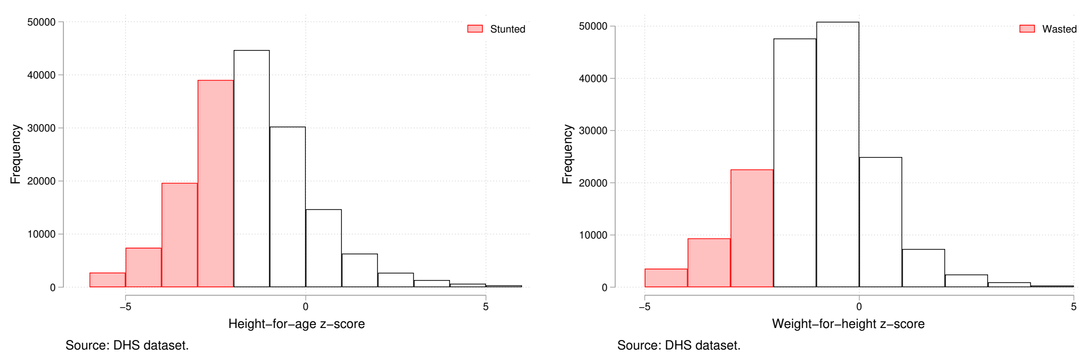
Notes: The dependent variable is the natural logarithm of annual crop yield (kg per hectare) from 2001 to 2015. The specification includes district and year fixed effects. The 5th decile is selected as reference.

Figure 2.2: Coefficient for rainfall deciles and 95% CI in India.



Notes: The missing in the map indicates the null values for union territory Lakshadweep. The dark lines in the background are the district borders.

Figure 2.3: The dots represent the average soil organic carbon content of the DHS rural clusters in India.

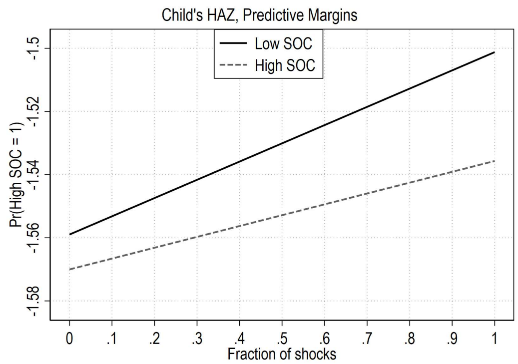


(a) Stunted (HAZ< -2)

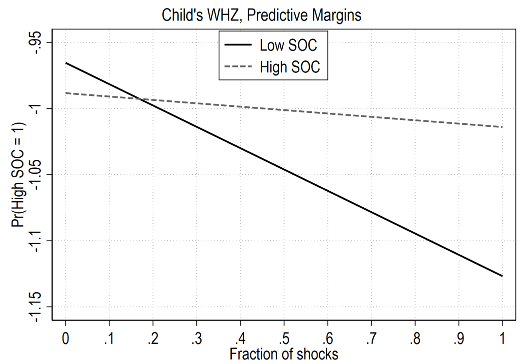
(b) Wasted (WHZ< -2)

Notes: Source: Own calculations based on DHS dataset (2015-2016).

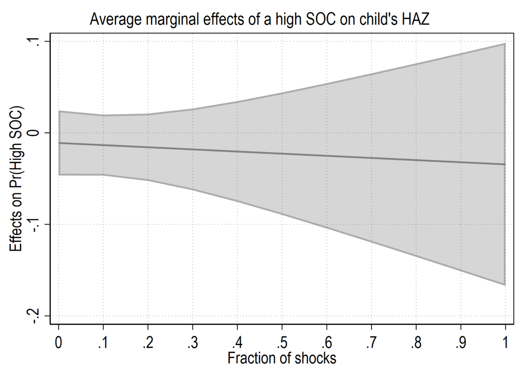
Figure 2.4: Distribution of childhood health outcomes.



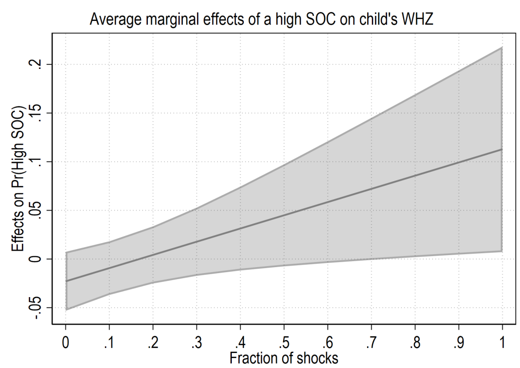
(a) Height-for-age z-scores



(b) Weight-for-height z-scores

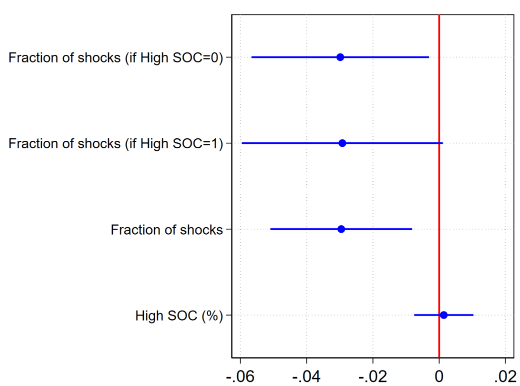


(c) Height-for-age z-scores

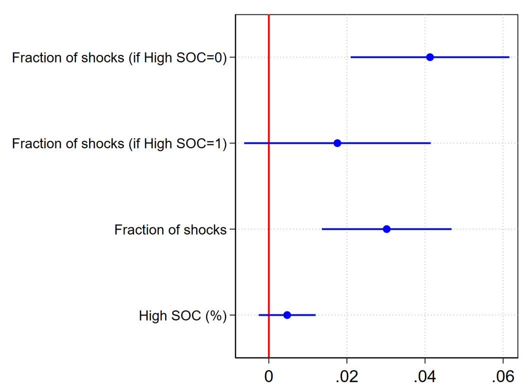


(d) Weight-for-height z-scores

Figure 2.5: Average marginal effects of high SOC levels on anthropometric measurements in childhood.



(a) Stunting



(b) Wasting

Notes: The x-axis is the probability level. The high SOC level is fixed above the 50th percentile.

Figure 2.6: Average marginal effects on the probability of childhood stunting and wasting.

Table 2.1: Summary statistics.

	Observation	Mean	Std. Dev.
Child health measures			
Height-for-age z score	169,904	-1.558	1.681
Weight-for-height z score	169,904	-0.991	1.381
Child health outcomes, yes=1			
Stunted (HAZ< -2)	169,904	0.405	0.491
Wasted (WHZ< -2)	169,904	0.209	0.406
Rainfall below 20th percentile, yes=1			
Rainfall shock - in-utero	169,904	0.110	0.313
Rainfall shock - birth year	169,904	0.110	0.312
Rainfall shock - 1st year	137,807	0.125	0.331
Rainfall shock - 2nd year	103,642	0.148	0.355
Rainfall shock - 3rd year	69,621	0.168	0.374
Rainfall shock - 4th year	33,951	0.167	0.373
Fraction of shocks	169,904	0.134	0.182
Soil health measure			
Soil organic carbon (SOC) %(g/Kg)	169,897	0.945	0.675
25th percentile level of SOC	169,904	0.633	
50th percentile level of SOC	169,904	0.733	
75th percentile level of SOC	169,904	0.965	

Note: The rain shock for the 1st to the 4th year have different observations to adjust the age of the child. The sample is composed of 33,951 4-year-olds, 69,621 3-year-olds, 103,642 2-year-olds, 137,807 1-year-olds and 169,904 in-utero. Source: DHS and CHIRPS data.

Table 2.2: Impact of high levels of SOC on the health of children.

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.058	-0.161***	0.011	-0.063
	(0.050)	(0.042)	(0.063)	(0.053)
High SOC (%)	-0.011	-0.023	-0.008	-0.023
	(0.018)	(0.015)	(0.021)	(0.018)
High SOC $\times$ Fraction of shocks	-0.023	0.136**	-0.071	0.057
	(0.072)	(0.059)	(0.089)	(0.071)
DHS controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	-1.558	-0.991	-1.573	-1.059
SD dependent var.	1.681	1.381	1.667	1.366
Observations	169,904	169,904	102,296	102,296
R-square	0.148	0.090	0.144	0.079

Levels of significance: p$< 0.01^{***}$, p$< 0.05^{**}$, p$< 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 50th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time.

Table 2.3: Heterogeneity by selected climate zones

	HAZ			
	Tropical wet	Tropical wet and dry	Semi arid	Humid sub-tropical
Fraction of shocks	-1.204	-0.167	0.130	0.062
	(1.661)	(0.167)	(0.130)	(0.061)
High SOC (%)	0.451	-0.009	0.023	-0.031
	(0.284)	(0.029)	(0.051)	(0.027)
High SOC × Fraction of shocks	1.084	0.175	-0.767**	0.052
	(1.661)	(0.183)	(0.322)	(0.094)
Mean dependent var.	-1.258	-1.538	-1.516	-1.647
Observations	7036	40,607	25,517	86,254
R-square	0.146	0.130	0.144	0.160

	WHZ			
	Tropical wet	Tropical wet and dry	Semi arid	Humid sub-tropical
Fraction of shocks	-0.325	0.292**	-0.280**	-0.133***
	(0.813)	(0.139)	(0.111)	(0.051)
High SOC (%)	0.314*	0.016	-0.054	-0.021
	(0.175)	(0.026)	(0.041)	(0.023)
High SOC × Fraction of shocks	0.200	-0.416***	0.547**	0.180**
	(0.819)	(0.153)	(0.275)	(0.075)
Mean dependent var.	-0.861	-1.197	-1.025	-0.934
Observations	7036	40,607	25,517	86,254
R-square	0.079	0.075	0.072	0.093

Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$, $p < 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. The high SOC level is fixed above the 50th percentile. Each regression includes district and month-birth year specific fixed effects. All regressions include demographic controls such as child, mother, and household level characteristics, and weather controls. Arid and Mountain are limited by very small sample to provide meaningful estimates and hence excluded.

Table 2.4: Heterogeneities on the full sample.

	Boys		Girls	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.011	-0.112**	0.108	-0.205***
	(0.065)	(0.057)	(0.067)	(0.055)
High SOC (%)	-0.023	-0.005	0.003	-0.041**
	(0.022)	(0.020)	(0.024)	(0.020)
High SOC × Fraction of shocks	0.022	0.110	-0.068	0.152**
	(0.093)	(0.079)	(0.094)	(0.077)
Mean dependent. var.	-1.597	-1.017	-1.516	-0.963
Observations	87,643	87,643	82,259	82,259
R-square	0.142	0.096	0.165	0.093

	Poor		Non-poor	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.060	-0.197***	0.056	-0.110*
	(0.069)	(0.056)	(0.069)	(0.060)
High SOC (%)	-0.000	-0.012	0.019	-0.029
	(0.026)	(0.022)	(0.024)	(0.020)
High SOC × Fraction of shocks	0.002	0.114	-0.038	0.133*
	(0.104)	(0.081)	(0.092)	(0.080)
Mean dependent. var.	-1.847	-1.135	-1.321	-0.873
Observations	76,633	76,633	93,259	93,259
R-square	0.128	0.088	0.137	0.090

	Has ag. land		Has no ag. land	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.083	-0.190***	0.033	-0.110*
	(0.063)	(0.054)	(0.075)	(0.062)
High SOC (%)	-0.015	-0.025	-0.006	-0.012
	(0.023)	(0.020)	(0.026)	(0.021)
High SOC × Fraction of shocks	-0.112	0.119	0.089	0.132
	(0.090)	(0.076)	(0.104)	(0.083)
Mean dependent. var.	-1.511	-0.976	-1.617	-1.009
Observations	94,065	94,065	75,838	75,838
R-square	0.152	0.100	0.153	0.089

Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$, $p < 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 50th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. See Appendix Table A10 for heterogeneities on the matched sample.

Table 2.5: Impact of high SOC on the likelihood of childhood stunting and wasting: Logit estimates.

	Full		Matched	
	Stunted	Wasted	Stunted	Wasted
Fraction of shocks	0.870**	1.309***	0.875*	1.091
	(0.056)	(0.088)	(0.070)	(0.094)
High SOC (%)	1.006	1.053**	1.002	1.038
	(0.023)	(0.027)	(0.027)	(0.031)
High SOC × Fraction of shocks	1.003	0.855	1.101	1.061
	(0.091)	(0.082)	(0.121)	(0.123)
AME of the shock fraction at a high SOC=1	-0.029*	0.017	-0.008	0.024
	(0.015)	(0.012)	(0.019)	(0.015)
AME of the shock fraction at a high SOC=0	-0.030**	0.041***	-0.029*	0.014
	(0.014)	(0.010)	(0.017)	(0.014)
DHS controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent var.	0.405	0.209	0.407	0.221
SD dependent var.	0.491	0.406	0.491	0.415
Observations	169,898	169,879	102,289	102,147

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Odd ratios are reported. Robust standard errors in parentheses are clustered at the DHS cluster level. The high SOC level is fixed above the 50th percentile. AME refers to average marginal effects. All regressions include demographic controls such as child, mother, and household level characteristics, and weather controls.

Chapter 3

Early-life exposure to drought on later-life disability

3.1 Introduction

According to the National Family Health Survey of India in 2015-2016, 18.2% of live births reported birth weights of less than 2.5 kilograms, compared to 22% in 2005-2006. Birth rates are an important predictor for short-term health indicators, including child mortality, and long-term health indicators, including educational and labour market outcomes [Black et al., 2007]. Low birth rates (as defined by the World Health Organization as any baby born under 2.5 kilograms) are associated with developing disabilities, particularly cognitive disabilities in children [Goisis et al., 2017]. In addition, extreme weather has been shown to adversely affect the mental health of children in low- and middle-income countries [Rother et al., 2021]. Studies have documented the relationship between climate change (increased hot days and decreased rainfall) and its impact on birth weight in both developed [Deschênes et al., 2009] and developing countries [Grace et al., 2015]. Food shortages caused by crop failure due to extreme weather conditions and, therefore, nutritional deprivation may negatively impact the birth weight of children [Grace et al., 2012, Heckman, 2007, Almond and Currie, 2011]. In this article, I examine how weather shocks during early childhood can affect the prevalence of disability in low- and middle-income countries setting, a context for which there is little related research.

For many disabilities, the causes of disability are often unknown, indicating the major gaps in existing disability research.[37] However, in the medical literature, cognitive and musculoskeletal disorders (locomotor system) are well documented and related to the birth weight of the child, which in turn is influenced by adverse weather conditions [Grace et al., 2015, Nübler et al., 2021]. Despite the potential linkage from weather to disability, this connection has not been shown in the

[37] According to the Rights of Persons with Disabilities Act, 2016, person with disability is defined as *"a person with long-term physical, mental, intellectual or sensory impairment which in, interaction with barriers, hinders his full and effective participation in society equally with others."* The "long term" covers a period of at least twelve months.

literature. Therefore, I investigate the impact of adverse weather conditions during early childhood on disability later in life.

The objective is to show that early exposure to periods of drought may increase the incidence of disability at birth or later in life. This paper provides new evidence on how exposure to drought early in life impacts disability rates later in life. The results suggest that early exposure to droughts increases the risk of disability in adults by 10%. Specifically, individuals are 10% more likely to have a locomotor (musculoskeletal) disability and 25% more likely to have cognitive impairments.

Following previous literature (e.g., Dinkelman [2017], Nübler et al. [2021]), I treat weather-related shocks as exogenous and estimate their causal impacts on the prevalence of disability rates. I exploit geographical and cohort variation in exposure to early-life weather shocks to estimate the prevalence of disability later in life. The results suggest that an increased prevalence of any type of disability in boys and girls exposed to drought during their childhood.

Much of this century is characterized by a significant global population affected by adverse weather events.[38,39] The most vulnerable population is in low- and middle-income countries that have limited resources to respond to climate change [Nübler et al., 2021]. Poverty may result in low birth weight and thus disability. People with disabilities in India are amongst the poorest and have disabilities at birth or under school age [O'Keefe, 2007].

Extensive literature has documented exposure to various early-life environmental factors for adverse effects on human health [Heckman, 2007, Maccini and Yang, 2009, Dinkelman, 2017, Rosales-Rueda, 2014, Singhal, 2019]. Feeny et al. [2021b] find that early-life exposure to adverse rainfall reduces the likelihood of women being employed in the formal sector in Vietnam. Singhal [2019] find that individuals who were exposed to the American war in Vietnam as children were more likely to develop a serious mental illness as adults. Adhvaryu et al. [2018] demonstrate in Mexico that adverse circumstances in early life often have long-term negative impacts on later life

[38]EM-DAT Public, available at https://public.emdat.be/mapping

[39]Appendix figure A.3 shows the incident of drought (rainfall below 20th percentile of long-run historical average) at district level between 1901-2016 in India.

and that timely political intervention in terms of transfer of funds could address disadvantages in early life.

While much is known about the connection between weather events and health outcomes, less is known about the impact on disabilities. Notable exceptions include Dinkelman [2017], who finds that, in South Africa, exposure to drought in early childhood increases later-life disability rates by up to 5 percent; and Rosales-Rueda [2014] who finds that parents in the United States are investing less in children with mental health conditions. I contribute to the literature by exploring the mechanisms underlying environmental factors in the effects of early childhood on young adolescents with disabilities.

3.2 Disability in India

Table 3.1 presents the share of disabled persons in urban and rural areas. The table provides the percentage of men and women with disabilities as a percentage of the population in 1981, 1991, 2002 and 2018.

Overall, the percentage of people with disabilities increased proportionately more in rural areas; more males with disabilities than females. Furthermore, the percentage has increased since 2002: 2.6% of men with disabilities in 2018, up from 2.1% in 2002. The percentage of women with disabilities has also increased since 2002: 2.0% in 2018, up from 1.6% in 2002.

According to the 58th round (2002) of the National Sample Survey (NSS), there are more people with disabilities in poor households in rural areas. Locomotor (musculoskeletal) disability is the most common type of disability, followed by visual disability. In 2002, households with disabilities had lower levels of education than the general population. Households with a hearing-impaired member are relatively better off among households with disabled members and households with a visual-impaired member appear to be worse off.

According to NSS data, the marital status of women with disabilities is significantly lower than in the general population: only 29% were currently married at the time of the survey in 2002 and

40% were never married, 5% more than in 1991. Women with disabilities have the highest rate of widowhood than the general population: 35% in 1991 and 29% in 2002.

Employment rates for people with disabilities were lower than for the general population, both urban and rural, and for both males and females. Approximately 35% were not able to work due to a disability and 10% of those who were able to work were self-employed in 2002. This reflects the serious economic consequences of Indian disability.

3.2.1 Disability-related aids and facilities

According to the 76th round (2018) of the Survey of Persons with Disabilities, about 23% of persons with disabilities were advised by a medical advisor to obtain aid or a device to help persons with disabilities. But only 17% of people have acquired the aid or device. The main reason is the affordability of obtaining aid or device.

With respect to locomotor disability, approximately 65% were not advised to use the aid or device by a medical consultant and the remainder who were advised to use only 24% acquired it. Similarly, approximately 33% and 21% have acquired vision and hearing impairment aids or devices. In addition, approximately 54% and 67% of respondents were not advised to use aids or devices for visual and hearing needs, respectively.

Of those who acquired any type of aids or devices related to a locomotor, visual, and hearing disability, about 72%, 88%, and 74% were purchased through household spending, respectively; 15%, 8%, and 22% were acquired by government assistance; and 13%, 4%, and 4% from other sources. Non-government organization as a source was limited and less than 5% for locomotor, visual, and hearing disability. In the case of speech and mental disability, the values regarding the aid or the device advised and acquired are not available.

Most persons with disabilities live with their spouse or other family members. Approximately 3% of people with disabilities live alone and less than 0.5% live in an institution or shelter. About 37% of people with disabilities need no caregiver and among those who need a mother or spouse provide the most care.

About 43% of disabled people use public transport and more than two-thirds of them have had difficulty accessing public transport. More than half of disabled people use public buildings such as schools and workplaces, and two-thirds of them have difficulty accessing buildings. The main challenges are the lack of infrastructure and the lack of accommodation for people with disabilities. These may include, for example, inaccessible steps or stairways and the unavailability of a ramp, grooved tiles or elevator, the unavailability of toilet seats, and the difficulty of reading signs for instructions, public announcements, etc.

3.3 Theoretical Framework

Extreme weather conditions can lead to low birth weight [Grace et al., 2015] and low birth weight infants are more likely to develop a disability [Goisis et al., 2017]. To model the relationship between early exposure to drought and the prevalence of disability later in life, I follow a model of human capability formulation similar to Heckman [2007] and Rosales-Rueda [2016]. Humans are assumed to have a vector of abilities at each age, including cognitive abilities, non-cognitive abilities, and health stocks [Heckman, 2007]. We modify the human capacity model for people with disabilities.

Under this model, the probability of disability status of individual i of age a living in district d, y_{iad} is given by

$$y_{iad} = f_a(\pi_{ad}, I_{ad}(\pi_{ad}, X_i, Z_h); \epsilon_{iad}) \tag{3.1}$$

where $y_{iad} = 1$ if person i is disabled at age a and 0 otherwise; π_{iad} is the share of years between in-utero to 4 years (6 years total) in which an individual in district d experienced an environmental shock. a is individual's age at the time of survey. This mechanism reflects direct impacts of heat/drought and does not account for investments.

Mathematically, π_{iad} is given by $\pi_{iad} = \frac{\sum_{t=-1}^{4} D_{adt}}{6}$, where D_{adt} is an indicator equal to 1 if district d experienced a drought when person i of age a was t years old where $t = -1$ is in-utero and $t = 0$ is birth year. It reflects the share of years from in-utero to age 4 in which a child experienced drought conditions. To make the interpretation easier, we provide an alternative definition of π_{adt}, which is a vector of environmental shocks from in-utero to age 4 for $t \in -1, 0, 1, 2, 3, 4$ where $t = -1$ is in-utero and $t = 0$ is birth year. Then, $\pi_{adt} = 1$ if an individual in district d of age a experienced a drought at age t and 0 otherwise.

Next, $I_{iad}(\pi_{ad}, X_i, Z_h)$ represent an investment in the individual i from in-utero to age a, where investments include mother's nutrition during pregnancy, occupational therapy, appliances or other aids for the disabled person, nutrition for the individual i, etc. I_{iad} depends on the environment affects earnings, consumption needs, etc. It also depends on individual characteristics, X_i, which include demographics (gender, age at survey (a), education level, older-age onset of disability (0,1), and on household characteristics, Z_h, which include rural/urban indicator, scheduled caste and tribe indicator, Hindu (indicator), household size (count), landholdings (indicator for smallholder)).

Finally, ϵ_{iad} are unobserved factors that influence the probability of person i of age a being disabled in district d. Some examples include genetic endowments, etc.

The effect of early-life environmental shocks, conditional on ϵ_{iad}, is

$$\frac{dy_{iad}}{d\pi_{ad}} = \frac{\partial f_a}{\partial \pi_{ad}} + \frac{\partial f_a}{\partial I_{iad}} \frac{\partial I_{iad}}{\partial \pi_{ad}} \tag{3.2}$$

The first element in the above right-hand side equation, $\frac{\partial f_a}{\partial \pi_{ad}}$, which is the direct effect of heat/drought exposure on disability status at age a, hypothesized to be > 0. It is a biological impact [Heckman, 2007]. A higher temperature during conception and later during pregnancy may cause lower birth weight, delayed locomotor development and cognitive impairments, and is also associated with infant mortality [Grace et al., 2015, Nübler et al., 2021, Banerjee and Maharaj, 2020].

The second element in the above right-hand equation, $\frac{\partial f_a}{\partial I_{iad}} \frac{\partial I_{iad}}{\partial \pi_{ad}}$, which is the indirect effect of heat/drought through its effect on income, economic outcomes, and investment choices, including nutrition. By assumption, $\frac{\partial f_a}{\partial I_{iad}} < 0$, that is, increased investment by parents can lead to a low probability of individual disability.

But $\frac{\partial I_{iad}}{\partial \pi_{ad}}$ is ambiguous because it depends on investment response to shocks. There may be trade-offs, in which the household invests more on disabled members than non-disabled members to compensate for the disability. In situation like these, the sign could be positive [Heckman, 2007, Rosales-Rueda, 2016]. In some cases, the household may invest more in a non-disabled member because the return on investment may be greater for a non-disabled member than for a disabled member. Then, the sign would be negative [Heckman, 2007, Rosales-Rueda, 2016]. Therefore, the sign of this indirect effect is also ambiguous.

3.4 Data and Descriptive statistics

I use Round 76 of the National Sample Survey Office's (NSS) Survey on Persons with Disabilities in 2018 (July to December). The NSS disability data represent a nationally representative data set. There are two major official sources of disability information: the NSS and the Census. While there is a difference between disability estimates from both sources. The NSS estimates were used in a report titled "People with Disabilities in India" by the World Bank's Human Development Unit. Publicly available Census disability data are aggregated at the state level. But for the purposes of this study, I need data on an individual basis. Therefore, I use the NSS data set where I observe disability information on an individual level.

3.4.1 Survey of Disabled Persons

For my analysis, I linked a large sample of cross-sectional data on persons with disabilities from the Indian Ministry of Statistics and Program Implementation to the historical climate events around their time of birth year.

National Sample Survey (NSS): 76th round (July-December 2018)

Detailed information was collected on five types of physical disabilities: locomotor disability, visual disability, hearing disability, speech and language disability, and other rare physical disabilities. The survey also includes information about mental disability. Moreover, the survey includes the cause of disability, aids/appliance acquired by the disabled, and the level of general and vocational education of the disabled. In addition, data on school enrolment were collected for persons with disabilities in the age group 3 to 35 years.

The 76th NSS round (2018) used a stratified multi-stage sampling design. Firstly, villages in rural areas and blocks in urban areas were randomly selected from the 2011 Census records. Within selected villages and urban blocks, households were stratified into seven second stage strata (SSS). The SSS1 was based on households with persons with rare disabilities.[40] SSS2 was formed from the remaining households, excluding SSS1 households, that have at least one person with a mental disability, and so forth. And, the last, SSS7 was formed from the remaining households without a disability.[41] Appendix Table A.24 shows the sample households by type of disability. Approximately 43% of surveyed households had at least one member with a locomotor (musculoskeletal) disability, followed by 11.2% of households with a mental disability. Visual impairment (9.2%), hearing loss (8.8%), speech and language impairment (7.8%) and rare impairment (4.8%) of the sample households are below 10%. About 15% of sampled households did not have any disabled members and these households become the comparison group. Since the Survey of Disabled Persons underestimates households without a disabled member, my results may be biased upward than the true effect.

To sum up, 5,378 rural villages and 3,614 urban blocks were identified across India for the 76th round of the NSS. Within selected villages 81,004 households were interviewed and 37,148 households in selected urban blocks. In all, 402,589 people were surveyed in rural areas and

[40]According to the NSS 76th round (2018), 11 rare disabilities have been identified as (i) acid attack victims, (ii) autism spectrum disorder, (iii) cerebral palsy, (iv) dwarfism, (v) haemophilia, (vi) multiple sclerosis, (vii) muscular dystrophy, (viii) other chronic neurological conditions, (ix) Parkinson's disease, (x) sickle cell disease, (xi) thalassemia.

[41]SSS3 was formed from the remaining households, excluding SSS1 and SSS2 households, who have at least one person with a speech and language disability. The SSS4 was constructed from the remaining households, excluding SSS1, SSS2 and SSS3 households, which have at least one visually impaired person. SSS5 was constructed from the remaining households, excluding SSS1, SSS2, SSS3 and SSS4 households that have at least one person with a hearing disability. SSS6 was formed from the remaining households after excluding SSS1, SSS2, SSS3, SSS4 and SSS5 households that have at least one person with a locomotor disability. SSS7 was formed from the remaining households without a disability.

173,980 in urban areas. 74,946 people with disabilities surveyed in rural settings and 19,248 in urban settings. I restrict the sample to individuals under 71 years old.[42]

3.4.2 Climate data

I use the monthly rainfall data grid of 0.5 degrees by 0.5 degrees from the Climate Research Unit (CRU) version 4.06, University of East Anglia. The version 4.06 of the CRU dataset covers the period 1901-2021 [Harris et al., 2020]. For my analysis, I aggregate the CRU data at annual rainfall and then construct the rainfall deciles (1-10). I define drought as annual precipitation in a given year that falls below the 20th percentile of the long-term historic average in the districts. Figure 3.1 shows the Indian map with the number of rainfall shocks by district between 1948 and 2018. I define rainfall shock as annual precipitation in any given year less than the 20th percentile of historic precipitation in the districts. Historical rainfall averages from 1901 to 2018. Additionally, Figure A.3 in the appendix illustrates the frequency of droughts in India. This shows that droughts are frequent and that heat waves last longer.

I combine climate data with the disability survey using district and year of birth data. Figure 3.2 shows drought exposure by cohort. We observe variation in drought exposure between the different cohorts.

3.4.3 Descriptive statistics

Table 3.2 presents the descriptive statistics used in this study. Approximately 8% of the sample have some kind of disability. The most common type of disability seen is locomotor disability (about 4.5%) followed by mental disability (1.4%) and all other disabilities are less than 1%. Speech and language impairments are the least common in the sample (under 0.5%). On average, people in this sample are 29 years of age. About 50% of the sample is female. Approximately 3% of the sample began disability at 36 years of age or older. Approximately 24% of individuals in the sample were exposed to drought while in the womb. Early childhood drought (in utero to age

[42]95% of the sample are under 70 years old.

4) shows that cohort members were exposed to droughts in approximately 1.206 years (0.201 x 6 = 1.206) in early life.

Figure 3.3 shows the kernel density of age at the onset of any disability. It shows a double peak, with the highest rate of disability at birth or shortly afterwards, and then between 50 and 60 years. According to the United Nations, elderly are at higher risk of disability as a result of accumulating risks of illness, injury and chronic illness for life.

3.5 Empirical strategy

I exploit the geographic and cohort variation in early-life exposure to drought to estimate the prevalence of disability later in life.

$$y_{iad} = \beta_0 + \beta_1 \pi_{iad} + \gamma X_i + \lambda Z_h + \mu_d + \phi_{sa} + \varepsilon_{iad} \tag{3.3}$$

where $y_{iad}, X_i, Z_h, \pi_{ad}$, as defined in the theoretical model. We also consider the alternative definition of the evironmental shock, π_{iadt}, also defined in the theoretical model.

For identification, we decompose ϵ_{iad} into

$$\epsilon_{iad} = \mu_d + \phi_{sa} + \varepsilon_{iad} \tag{3.4}$$

where μ_d is a district fixed effect that controls for time-invariant district characteristics; ϕ_{sa} is an state-age (equivalent to a state-birth year) fixed effect that controls for state level heterogeneity.[43]

The unit of measurement is the individual-level disability outcomes. Drought is measured at the district level. To allow for the correlation of error terms between birth districts and year of birth, I follow Dinkelman [2017] and cluster standard errors at the district of birth and year of birth level. The validity of the OLS estimator, β_1, is based on the assumption that the indicator of drought status is exogenous. Since β_1 is the net effect of the biological mechanism and the investment

[43] Indian states are responsible for delivering services and commitments to people with disabilities.

mechanism. There may be some concern that the investment mechanism on the disability situation may be correlated with the ommitted variables.

3.5.1 Extension: Exploring the investment mechanism

The regression is carried out on the subset of the sample: households with one or more disabled members.

$$I_{iad} = \psi_0 + \psi_1 \pi_{iad} + \gamma X_i + \lambda Z_h + \mu_d + \phi_{sa} + \varepsilon_{iad} \tag{3.5}$$

where I_{iad} is the probability that the disabled individual i has at least one aid/device to assist persons with disabilities. The terms are defined as in Equation 3.3.

3.5.2 Potential threats to identification

One of the main threats to the identification of the impact of early exposure to drought is the potential sample selection bias due to selective mortality and fertility. The presence of selective mortality means that my sample will be biased towards children who survived the adverse shock in early life. Furthermore, the presence of selective fertility (i.e., to delay the family planning decision in response to the drought), then I underestimate the true negative impact of drought exposure in the early-life.

To assess whether these potential sample selection biases are present in my sample, I regress the cohort size and the ratio of women to men on drought exposure in-utero, controlling for district and year of birth fixed effects. The cohort refers to children born within a district within a year. Appendix Table A.25 presents the results. I find no effect of in-utero drought exposure on gender ratio, suggesting that selective fertility bias is not a major concern in my sample. However, the coefficient estimate for the cohort size is positive and statistically significant at the 5% significance level. This shows that cohort size has increased, that births have increased, during periods of low precipitation.

3.6 Results

Table 3.3 shows the effect of exposure to early-life drought on disability in later life. Dependent variables are binary (1 for persons with a disability; 0 otherwise). The sample includes people with a disability at birth and those who became disabled later in life. The sample excludes persons with disabilities due to injury or accident, as well as persons with multiple disabilities.[44] The results show 0.9 percentage points (a 10% increase over the sample average) an increased likelihood of any type of disability due to drought conditions. The results also show 0.5 percentage points (a 10% increase over the sample average) an increased likelihood of locomotor disability. The findings suggest no effect of cumulative exposure to early drought on the types of disability: visual, hearing, and speech. Point estimates for these types of disabilities are not statistically different than 0.

In the medical literature, early childhood (in-utero up to age 4) is considered as the critical stage of human development. Exposure to shock at this critical stage can result in any type of disability. Figure 3.4 shows the impact of timing of early exposure to drought on disability in the future. The results suggest that periods of droughts in-utero and 4 years are particularly harmful. I also examine the effects of drought in the first 10 years. Figure A.4 in the appendix shows the effects of drought on the first ten years. I find that exposure to droughts at age 5 and later has no impact on disability later in life. While the literature (e.g., Nübler et al. [2021]) links in-utero environmental shock with disability in later life, the fourth year is a matter of future research.

Next, I explore the investment mechanism. Table 3.4 shows the effect of early exposure to drought on the likelihood that the disabled individual has at least one aid/device. The regression is carried out on the subset of the sample: households with one or more disabled members. Dependent binary variables include: whether the aid/device was advised and whether the aid/device was acquired. Column 1 of Table 3.4 shows that early exposure to periods of drought increases the likelihood that a person will be advised on aid or equipment. The results indicate that individuals exposed to drought early in life are more likely to need to use the aid or device. Column 2 shows

[44]The appendix table A.26 presents the results for people with more than one disability. The results are unchanged from the main results.

that exposure to drought has no impact on the acquisition of aid or application to help people with disabilities.

Next, I explore the effect of drought on disability at birth and disability later in life. Table 3.5 presents the results. Each column shows the results for a separate regression. Column 1 excludes disabled persons whose disability is not apparent at birth and column 2 excludes disabled persons at birth. The results do not suggest any effect of drought on disability at birth, but periods of drought have affected disability after birth. The point estimate in column 2 is small and statistically insignificant at the 5% significance level.

Then, I interact an indicator of old age onset of disability in the main specification. I construct a dummy variable for old age, 1 for persons with disabilities whose disability occurred at age 36 or older and 0 otherwise. Table 3.6 presents the results. The drought coefficient shows that periods of drought have had a significant effect on persons with disabilities who became disabled before the age of 35. The interaction term, Drought*Old age, shows that the effect for people with disabilities who became disabled after the age of 35 was different than for people with disabilities who became disabled before the age of 35. Point estimate is negative and statistically significant at a significance level of 5%. The p-value in the row shows the joint hypothesis test for drought and drought*old age. The p-value is high suggesting that the onset of disability before 35 and after 35 is statistically the same.

To check the sensitivity of my results, I control for extreme precipitation in the main specification. I define extreme precipitation as annual precipitation in any given year above the 80th percentile of historical district precipitation. Appendix Table A.27 presents the results. The cumulative drought coefficient is similar to the main results. In addition, cumulative extreme rain is positively associated with vision impairment later in life. The point estimate is small and statistically significant at the 5% significance level. The results also suggest that extreme precipitation periods can reduce the likelihood that speech and language, and mental illness will be imperfect later in life. These results may not be explained by food pathways, but by non-food pathways, including the occurrence of diseases such as diarrhea and febrile during the extreme season. The results present an avenue for future research.

3.6.1 Mental disability

I see distinct categories of mental illness and cognitive impairment in the recent Survey of People with Disabilities (2018).[45] Recent literature (e.g., Nübler et al. [2021]) supports the linkage between the environment and human biology, particularly, that exposure to drought reduces the cognitive skills (i.e., the psychological result of perception and learning and reasoning). This can be due to nutritional pathways.

Table 3.7 presents the results. The results suggest that exposure to periods of drought during childhood is positively associated with cognitive impairment later in life. The point estimate is 0.4 percentage points (an increase of 25% over sample mean) and statistically significant at 5% significance level. Column 2 suggest that cumulative exposure to drought does not have an impact on mental illness later in life.

3.6.2 Heterogeneity by gender

Males are more sensitive to early life shocks compared to females [Almond and Currie, 2011]. This may be due to many channels, first, the biological channel, the medical literature (e.g. Di Renzo et al. [2007]) indicates that the male fetus requires higher levels of nutrients to grow. Second, the intra-household channel suggests that female children after birth are disadvantaged because of the preference given to the son among Indian families. During periods of low rainfall, the amount of nutrients available for child development is limited, which may lead to the development of any form of disability. Also within these limited resources male nutrition are preferred.

[45] Mental illness relates to (a) if respondent has unnecessary and excessive concerns and anxiety, repetitive behaviors and thoughts, mood swings or mood swings, speaks or laughs to self, staring into space; (b) whether it is having unusual experiences of listening to voices, seeing visions, a strange smell or feeling or a strange taste; and (c) experiencing unusual behavior or difficulty interacting and adapting. Cognitive impairment relates to (a) respondent has difficulty in understanding or communicating in your everyday activities; and (b) whether having difficulty understanding, understanding or communicating in reasoning, making decisions, correcting learning, problem solving.

To test the heterogeneity by gender, I interact an indicator for females in the equation 3.3. Table 3.8 shows the impact of early-life exposure to drought on late-life disability for both males and females. The drought coefficient shows that exposure to drought also significantly affects males. The interaction term, Drought*Female, indicates that the effect of drought exposure for females was different than for males. The point estimate is statistically insignificant at 5% significance level. The p-value in the row shows the joint hypothesis test for drought and drought*Female. The p-value is low, suggesting that the impact of drought exposure on disability later in life for males and females is statistically different.

3.6.3 Heterogeneity by climate zone

The effect of periods of low rainfall on agricultural production and therefore on food availability may be associated with different climatic zones. Following Dimitrova and Bora [2020], I constructed six major climate zones at the district level based on the basis of the climate classification Köppen Geiger.[46] They are tropical wet, tropical wet and dry, arid, semi-arid, humid sub-tropical, and mountainous. The Koppen classification map is based on local vegetation that, in turn, is based on local rainfall and temperature. The tropical rain forest and the tropical monsoon are reclassified as tropical wet whereas, the tropical savanna is reclassified as tropical wet and dry. The wet season in summer and the dry season in winter are characteristics of the tropical wet and dry zone. See Appendix A.5 for a map of the main climatic zones in India.

Multiple states may have one or more climate zones. I take that into account in the main specification by including state fixed effects. Table 3.9 shows the impact of early exposure to drought on adult disabilities by climatic zone. The tropical wet is a reference climate zone. Wet and dry tropical and humid subtropical coefficients show an increased likelihood of any type of disability. The Semi-Arid coefficient also shows an increased likelihood of any type of disability. These results indicate the mechanisms of the food and non-food pathways involved. Cumulative exposure to drought is negatively associated with any form of disability in wet and dry tropics and

[46]I am grateful to Anna Dimitrova for sharing the data and code with me.

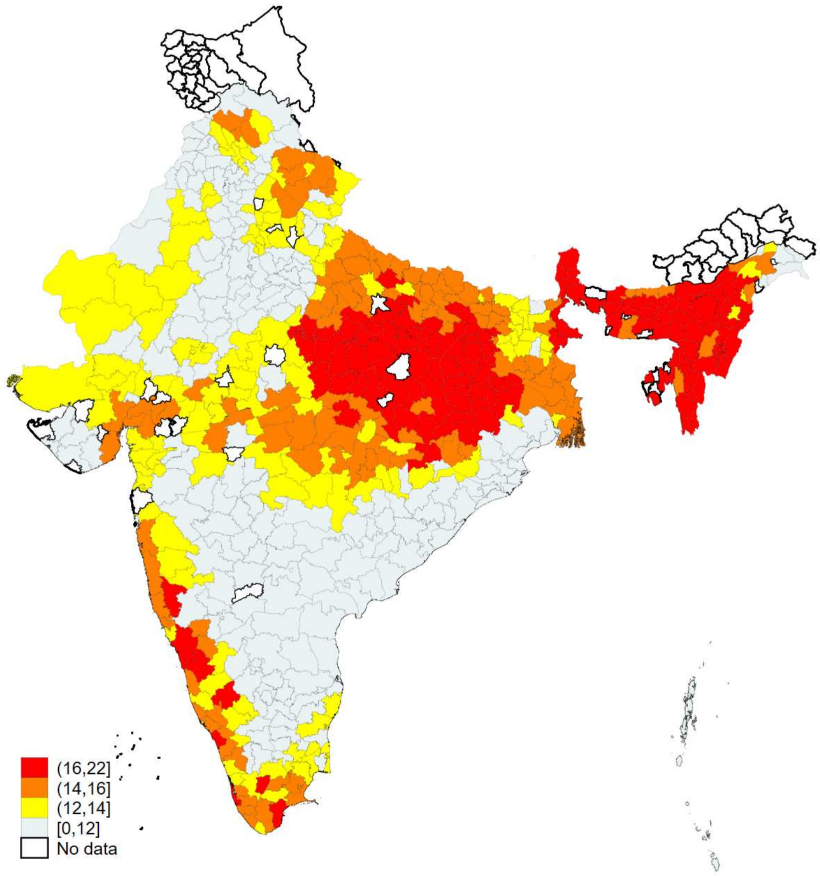
humid subtropics. Furthermore, humid tropical and subtropical zones may be associated with the disease environment and periods of low rainfall may reduce that disease environment.

I do robustness checks at different base levels (use tropical wet and dry as the reference category). Appendix Table A.28 reports the results. The results suggest that exposure to drought in early-life increases disability in the humid tropical climate area.

3.7 Conclusion

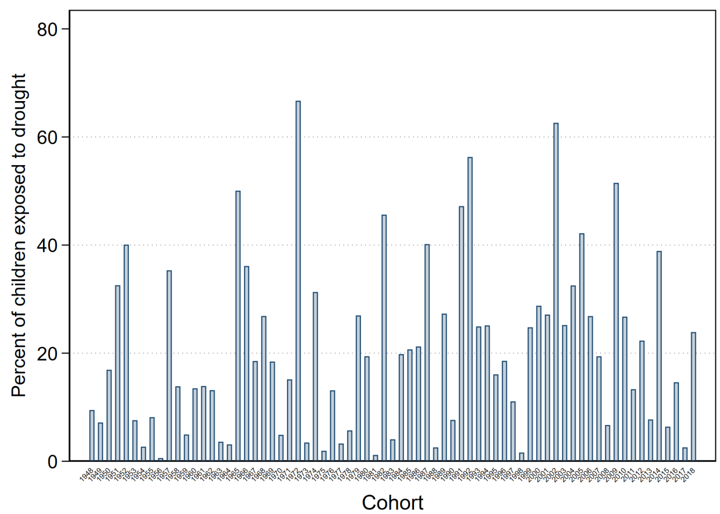
The paper provides new evidence on weather shocks during early childhood on prevalence of disability in low- and middle-income countries setting, a context for which there is little related research. The results suggest that early exposure to droughts increases the risk of disability in adults by 10%. Specifically, 10% more likely to have locomotor disorders and 25% more likely to have cognitive disabilities. I also find that there is a significant heterogeneity by gender, and women are at a disadvantage from drought impacts. It is worth noting that periods of low precipitation can also reduce the disease environment, diarrhea and febrile diseases in the tropics and subtropics. I contribute to the literature by exploring the mechanisms underlying these effects among young adolescents with disabilities. A healthy and able workforce is key to growing the economy. My results provide some suggestive evidence that any form of disability may be reduced later in life by ensuring food and nutrition, particularly during periods of drought when food availability is limited.

My research has some limitations. First, the disability observed in a survey is based on a self-reported health assessment, which may bias my results. Second, negative attitudes towards disability and the social stigma associated with disability can lead to false or under-reporting of disability outcomes, resulting in a measurement error. Nonetheless, my results suggest that the onset of disability at birth or later in life due to drought can be prevented through government interventions. Policies to avoid disability at birth must aim to ensure food and nutrition security in areas severely affected by drought. In addition, persons with disabilities need access to facilities, particularly in drought-prone areas, such as occupational therapies, which allow them to participate equally in society.



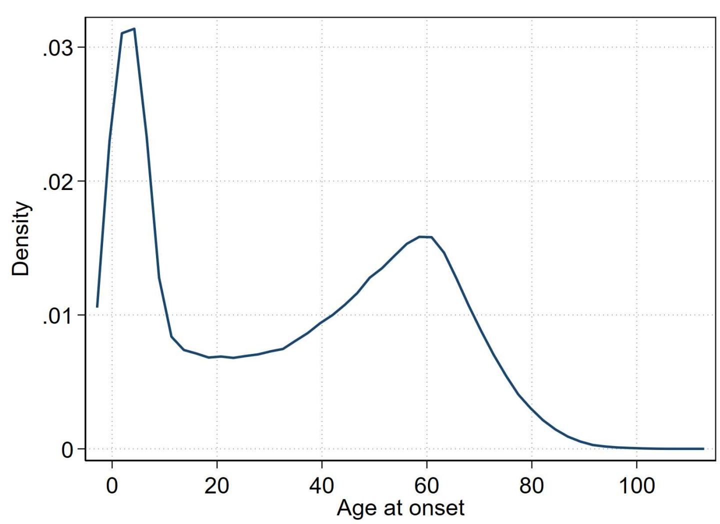
Notes: Indian districts are color-coded to distinguish the different drought incidence counts from 1948 to 2018. I define rainfall shock as annual precipitation lower than the 20th percentile of historic district precipitation. Source: Own calculation based on CRU dataset.

Figure 3.1: Number of rainfall shocks during 1948 - 2018.



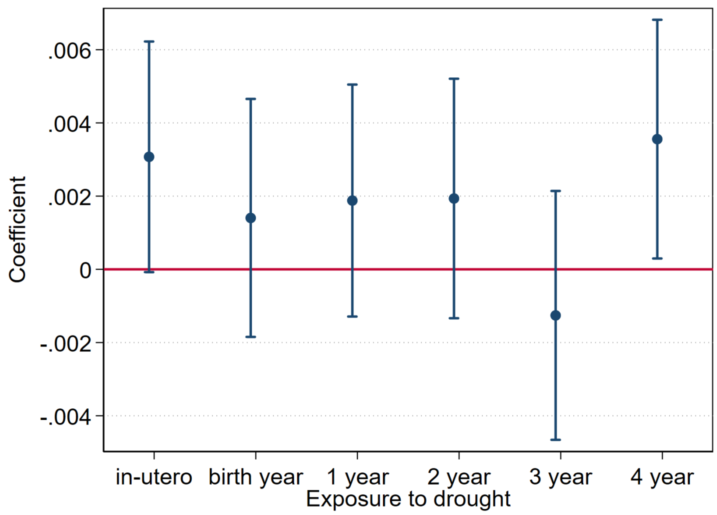
Notes: The y-axis shows the percentage of children exposed to drought during their birthyear. The x-axis shows the birthyear from 1948 to 2018. Source: Own calculation based on NSS 76th round (2018) and CRU data.

Figure 3.2: Drought exposure by cohort.



Source: Own calculation based on NSS 76th round (2018).

Figure 3.3: Kernel density of age at onset of all disability



Notes: Coefficient of disability outcomes on the timing of exposure to drought and 95% CI.

Figure 3.4: Impact of timing of drought exposure on the prevalence of any disability.

Table 3.1: Percentage of persons with disability in the population

	1981		1991		2002		2018	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Male	1.5	2.0	1.8	2.3	1.7	2.1	2.1	2.6
Female	1.3	1.6	1.4	1.7	1.3	1.6	1.8	2.0
All	1.4	1.8	1.6	2.0	1.5	1.8	2.0	2.3

Source: Various rounds of the national sample survey of India [O'Keefe, 2007].

Table 3.2: Descriptive statistics (N = 479,448)

	Mean	Std. Dev.
Disability outcomes		
Any disability	0.087	0.283
Visual disability	0.008	0.088
Hearing disability	0.006	0.075
Speech and language disability	0.003	0.053
Locomotor disability	0.045	0.207
Cognitive impairment	0.014	0.118
Mental illness	0.012	0.107
Weather shock		
Drought in-utero	0.241	0.428
Fraction of infancy (in-utero to age 4) in drought	0.227	0.198
Individual characteristics		
Age in years	29.159	18.561
Female	0.494	0.500
Education (higher secondary and above)	0.159	0.366
Household characteristics		
Rural	0.704	0.456
Schedule Castes and Tribes	0.302	0.459
Household size	6.211	2.851
Hindu	0.777	0.416
Land holdings (less than 1 ha)	0.850	0.357

Note: The sample excludes persons with disabilities due to injury or accident, as well as persons with multiple disabilities.

Table 3.3: Impact of early-life exposure to drought on later-life disability

	(1) Any disability	(2) Visual	(3) Hearing	(4) Speech	(5) Locomotor
Drought	0.009***	-0.0003	0.0001	0.001	0.005**
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Individual characteristics					
Female	-0.027***	-0.001***	-0.001***	-0.002***	-0.015***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Higher education	-0.053***	-0.004***	-0.003***	-0.003***	-0.011***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Household characteristics					
Rural	-0.001	0.000	0.001***	0.000	-0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Household size	-0.011***	-0.001***	-0.001***	-0.0001***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SC/ST	0.001	0.001***	0.001**	0.000	0.004***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Land holdings					
Less than 1 ha	0.005***	0.001**	0.001**	-0.000	0.004***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
District FEs	Yes	Yes	Yes	Yes	Yes
State-Birth year FEs	Yes	Yes	Yes	Yes	Yes
Mean dependent var.	0.091	0.009	0.007	0.003	0.049
Observations	453,418	415,745	414,717	413,293	433,395
R-square	0.056	0.034	0.028	0.011	0.047

Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$, $p < 0.1^{*}$. Robust standard errors in parentheses are clustered on year of birth and at the district level. Each column presents results from a separate regression. The sample includes individuals with a disability at birth. "Any disability" includes all types of physical and mental disability. Columns 2 to 5 exclude all other types of disabled people.

Table 3.4: Effect of early-life exposure to drought on advised and acquired disability-related aids or appliance

	(1) Whether aid/device was advised	(2) Whether aid/device was acquired
Drought	0.003^{*}	0.0003
	(0.002)	(0.002)
District FEs	Yes	Yes
State-Birth year FEs	Yes	Yes
Mean dependent var.	0.023	0.017
Observations	386,130	386,130
R-squared	0.151	0.121

Levels of significance: $p < 0.1^{*}$. Robust standard errors in parentheses are clustered on year of birth and at the district level. Each column presents results from a separate regression. The regression is carried out on the subset of the sample: households with one or more disabled members. Dependent variables include binary (0/1). Control variables include gender indicator, age education level, household type (rural/urban), social group, household size and land area.

Table 3.5: The effect of drought on disability at birth and disability later in life.

	(1) Any disability at birth	(2) Any disability after birth
Drought (in-utero)	0.001	
	(0.001)	
Drought		0.004
		(0.003)
District FEs	Yes	Yes
State-Birth year FEs	Yes	Yes
Mean dependent var.	0.029	0.065
Observations	450,568	440,744
R-square	0.024	0.075

Levels of significance: $p < 0.1^{*}$. Robust standard errors in parentheses are clustered on year of birth and at the district level. Each column presents results from a separate regression. Column 1 excludes people with disabilities whose onset of disability is not at birth and column 2 excludes people with disabilities at birth. Control variables include gender indicator, age, education level, household type (rural/urban), social group, household size and land area.

Table 3.6: Heterogeneity due to disability in old age.

	Any disability
Drought	0.009***
	(0.003)
Old age	0.942***
	(0.001)
Drought x Old age	-0.009**
	(0.005)
P-val: Drought + Drought x Old age	0.945
District FEs	Yes
State-Birth year FEs	Yes
Mean dependent var.	0.091
Observations	453,418
R-square	0.302

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered on year of birth and at the district level. Old age is a dummy variable, 1 for disabled persons whose onset of disability occurred at age 36 and older. Control variables include gender, education level, household type, social group, household size and land size.

Table 3.7: Impact of early-life exposure to drought on later-life disability

	(1) Cognitive impairment	(2) Mental illness
Drought	0.004**	0.0002
	(0.002)	(0.001)
District FEs	Yes	Yes
State-Birth year FEs	Yes	Yes
Mean dependent var.	0.016	0.013
Observations	418,601	417,549
R-square	0.022	0.018

Levels of significance: $p< 0.05^{**}$. Robust standard errors in parentheses are clustered on year of birth and at the district level. Each column presents results from a separate regression. Columns 1 to 2 exclude all other types of disabled people. Control variables include gender indicator, age, education level, household type (rural/urban), social group, household size and land area.

Table 3.8: Heterogeneity by gender.

	Any disability
Drought	0.007*
	(0.004)
Female	-0.028***
	(0.001)
Drought x Female	0.004
	(0.004)
P-val: Drought + Drought x Female	0.002
District FEs	Yes
State-Birth year FEs	Yes
Mean dependent var.	0.091
Observations	453,418
R-square	0.056

Levels of significance: p$< 0.01^{***}$, p$< 0.05^{**}$, p$< 0.1^{*}$. Robust standard errors in parentheses are clustered on year of birth and at the district level. Female is a dummy variable. Control variables include age, education level, household type (rural/urban), social group, household size and land area.

Table 3.9: Heterogeneity by climate zone

	Any disability
Drought	0.020***
	(0.007)
Tropical wet and dry	0.011***
	(0.002)
Arid	0.003
	(0.004)
Semi-arid	0.015***
	(0.003)
Humid sub-tropical	0.006**
	(0.003)
Mountain	0.006
	(0.009)
Drought x Tropical wet and dry	-0.021**
	(0.008)
Drought x Arid	-0.011
	(0.014)
Drought x Semi-arid	-0.015*
	(0.009)
Drought x Humid sub-tropical	-0.017**
	(0.008)
Drought x Mountain	-0.012
	(0.023)
State FEs	Yes
Birth year FEs	Yes
P-val: Drought + Drought x Climate zone	0.097
Mean dependent var.	0.091
Observations	453,429
R-squared	0.295

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered on year of birth and at the district level. Tropical wet is a reference climatic zone. Control variables include gender indicator, age, education level, household type (rural/urban), social group, household size and land area.

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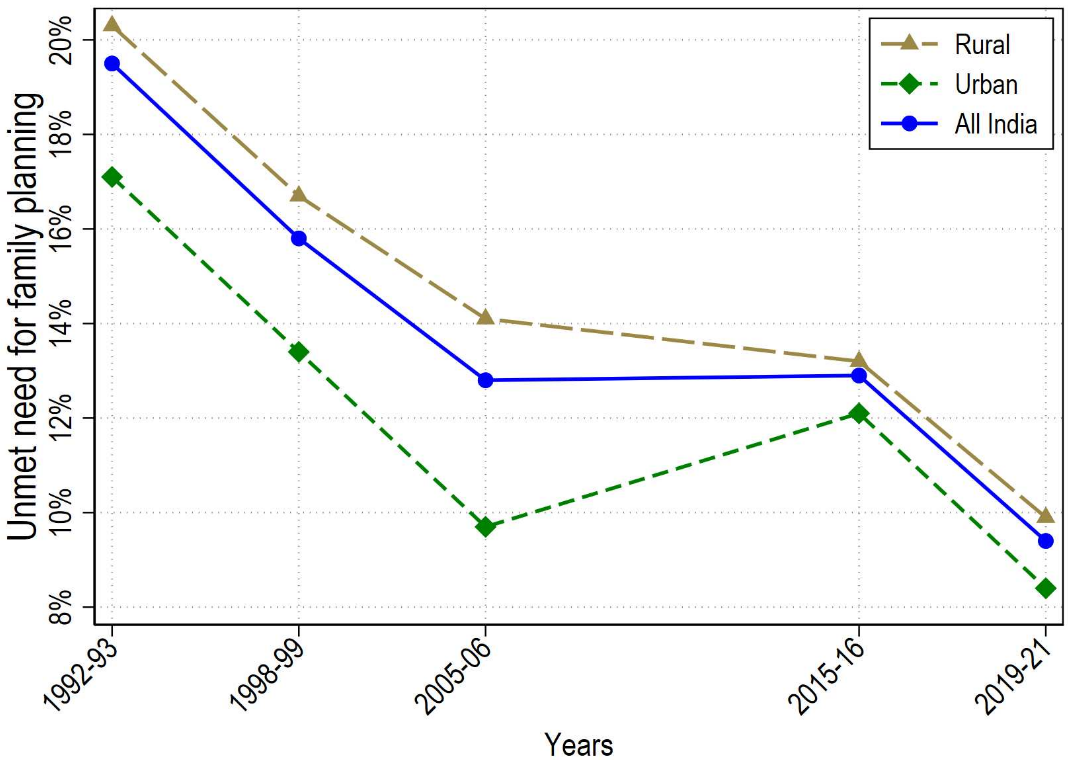
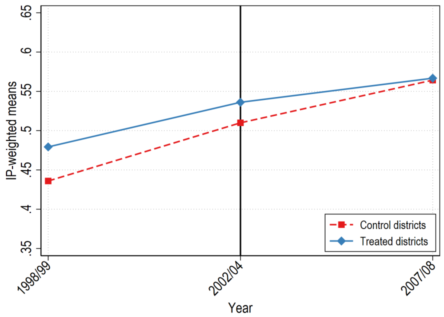
Appendix A

Additional Figures and Tables

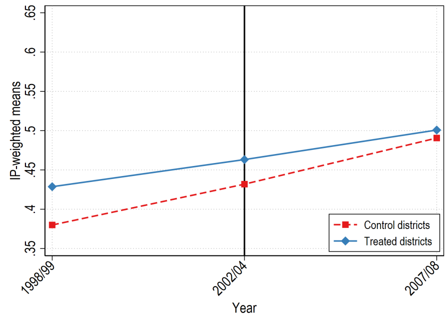


Notes: Source: Various rounds of National Family Health Survey.

Figure A.1: Unmet need of currently married women for family planning.



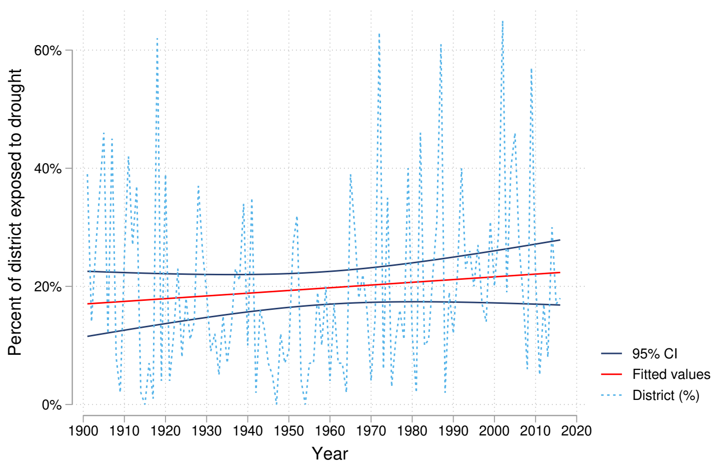
(a) Any methods



(b) Any modern methods

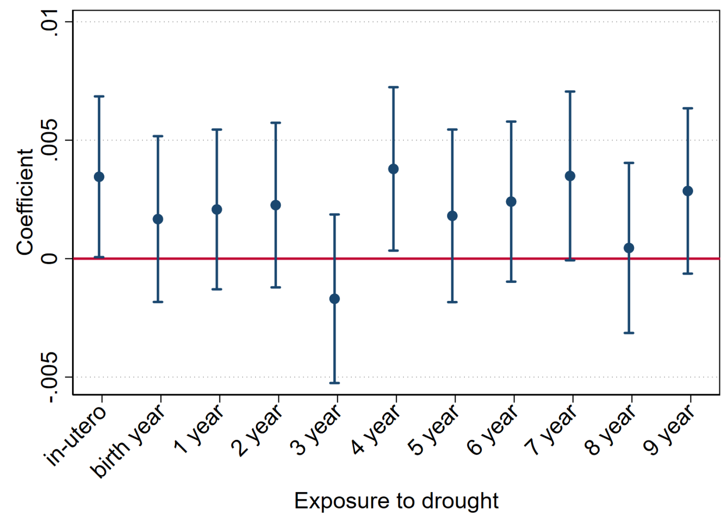
Note: The y-axis measures the average means from the pre-program: DLHS round 1 (1998/99) and round 2 (2002/04) and post-program: DLHS round 3 (2007/08). The IP-weighted mean is restricted to common support region.

Figure A.2: Pre-program trends in the use of family planning methods



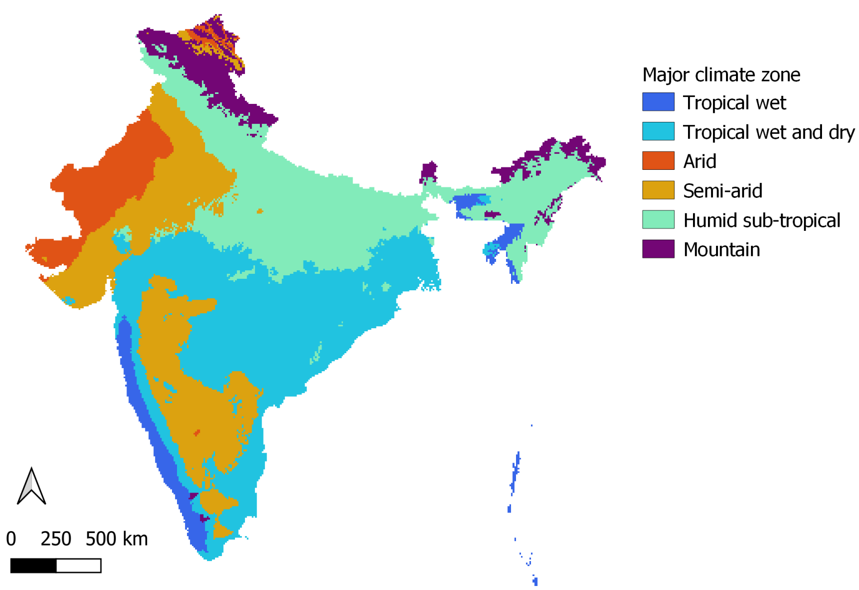
Notes: Incidence of drought (rainfall below 20th percentile of long-run historical average) at the district level (based on 2011 India Census district geographic boundaries) between 1901-2016. (Source: CRU)

Figure A.3: Frequency of drought events.



Notes: Coefficient of disability outcomes on the timing of exposure to drought and 95% CI.

Figure A.4: Robustness check: Including 10 years of early life.



Notes: Many states may have one or several climatic zones. Source: Own calculation.

Figure A.5: Major climate zones in India based on Köppen Geiger climate classification.

Table A.1: Logistic regression predicting treatment

	Treatment
Total Population	1.000***
	(0.000)
Percent rural	186.748***
	(7.485)
Area (in square km)	1.000***
	(0.000)
Percent Scheduled Castes	1905.793***
	(111.530)
Percent Scheduled Tribes	123.363***
	(2.849)
Percent Literate	0.074***
	(0.003)
Average MPCE	0.999***
	(0.000)
Average casual wage	0.995***
	(0.000)
Labor force participation rate	0.030***
	(0.002)
Female labor force participation rate	8.851***
	(0.657)
Rainfall (mm)	1.000***
	(0.000)
Growing degree days	1.000***
	(0.000)
Observations	631,152

Note: Standard errors are in parentheses. Odds ratios are reported.

Table A.2: Individual Summary Statistics before matching

	Pre-Program (2002-2004)		
	Treated	Control	Diff. (*p*-value)
Outcomes			
Any family planning methods	0.500	0.589	0.000
	(0.500)	(0.492)	
	[168,230]	[115,579]	
Any modern methods	0.428	0.512	0.000
	(0.495)	(0.499)	
	[168,230]	[115,579]	
Any traditional methods	0.072	0.077	0.506
	(0.259)	(0.267)	
	[168,230]	[115,579]	
Among women who are currently taking contraceptives.			
Female sterilization	0.681	0.660	0.321
	(0.466)	(0.474)	
	[84,126]	[68,082]	
Male sterilization	0.022	0.018	0.378
	(0.148)	(0.135)	
	[84,126]	[68,082]	
Intrauterine Device (IUD)	0.022	0.045	0.000
	(0.147)	(0.208)	
	[84,126]	[68,082]	
Oral pills	0.075	0.063	0.134
	(0.263)	(0.242)	
	[84,126]	[68,082]	
Condom	0.051	0.079	0.000
	(0.220)	(0.270)	
	[84,126]	[68,082]	
Rhythm/Periodic abstinence/Withdrawal	0.126	0.125	0.901
	(0.332)	(0.330)	
	[84,126]	[68,082]	

Note: Standard deviations are in parentheses. Observations are in square bracket. Treated includes phase one and two districts, and control includes phase three districts. The third column, the difference, is computed using OLS regressions and standard errors clustered at the district level. Source: DLHS round 2 (2002-2004).

Table A.3: Effect of MGNREGA on the use of family planning methods by female labor force participation rate: Triple difference

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post x High Female LFPR	-0.004	-0.003	-0.00003
	(0.015)	(0.014)	(0.011)
MGNREGA x Post	0.020	0.015*	0.004
	(0.012)	(0.009)	(0.010)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.558	0.486	0.072
SD dependent variable	0.497	0.500	0.259
Observations	570,193	570,193	570,193
Number of districts	480	480	480
R-square	0.220	0.227	0.091

Note: Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is restricted to common support and excludes current pregnant women. WLS estimator is used across all regressions. All regressions include controls at the individual and household level. See note to Table 1.4 for other details.

Table A.4: Effect of trimming at the fifth centile on the IP-weighted estimate

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post	0.020*	0.019*	0.002
	(0.011)	(0.010)	(0.006)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.582	0.512	0.070
SD dependent variable	0.493	0.500	0.256
Observations	297,492	297,492	297,492
Number of districts	252	252	252
R-square	0.204	0.227	0.121

Note: Levels of significance: p< 0.01^{***}, p< 0.05^{**}. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is cut at the 5th percentile. WLS estimator is used for all regression. All dependent variables are binary (1/0). Controls at the individual and household level are included in every regression. Any methods refer to individuals who are currently using any family planning methods. Modern methods include sterilization of women and men, IUDs/copper-t/loop, oral pills, male and female condoms, and others. Traditional methods include using rhythm, periodically abstinence, withdrawal, and others.

Table A.5: Effect of MGNREGA on the use of family planning methods: Unweighted results

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post	0.025***	0.021***	0.004
	(0.008)	(0.006)	(0.005)
Individual-level and household controls			
Women age in years	0.015***	0.015***	-0.0002**
	(0.0004)	(0.0004)	(0.0001)
Women can read or write	0.060***	0.046***	0.014***
	(0.003)	(0.003)	(0.001)
Spouse can read or write	0.056***	0.049***	0.008***
	(0.002)	(0.002)	(0.001)
Number of children	0.044***	0.038***	0.006***
	(0.002)	(0.002)	(0.0004)
Religion: Hindu	0.104***	0.102***	0.002
	(0.006)	(0.007)	(0.002)
Scheduled castes/tribes	-0.048***	-0.045***	-0.003**
	(0.003)	(0.003)	(0.001)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.554	0.481	0.073
SD dependent variable	0.497	0.500	0.260
Observations	630,173	630,173	630,173
Number of districts	480	480	480
R-square	0.218	0.227	0.090

Note: Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). OLS estimator is used for all regression. All dependent variables are binary (1/0). Any methods refer to individuals who are currently using any family planning methods. Modern methods include sterilization of women and men, IUDs/copper-t/loop, oral pills, male and female condoms, and others. Traditional methods include using rhythm, periodically abstinence, withdrawal, and others.

Table A.6: Regression results for various econometric specifications

	Any methods	Any modern methods	Any traditional methods
Panel A: without controls			
MGNREGA x Post	0.029***	0.025**	0.004
	(0.008)	(0.007)	(0.005)
Mean dependent variable	0.554	0.481	0.073
SD dependent variable	0.497	0.500	0.260
Observations	631,148	631,148	631,148
Number of districts	536	536	536
R-squared	0.113	0.131	0.088
Panel B: with controls			
MGNREGA x Post	0.025***	0.021***	0.004
	(0.008)	(0.006)	(0.005)
Mean dependent variable	0.554	0.481	0.073
SD dependent variable	0.497	0.500	0.260
Observations	630,173	630,173	630,173
Number of districts	536	536	536
R-squared	0.218	0.227	0.090
Panel C: without controls (match)			
MGNREGA x Post	0.019**	0.015**	0.004
	(0.008)	(0.007)	(0.005)
Mean dependent variable	0.558	0.485	0.072
SD dependent variable	0.497	0.500	0.259
Observations	571,076	571,076	571,076
Number of districts	480	480	490
R-squared	0.122	0.138	0.090
Panel D: with controls (match)			
MGNREGA x Post	0.018**	0.014**	0.004
	(0.008)	(0.006)	(0.005)
Mean dependent variable	0.558	0.486	0.072
SD dependent variable	0.497	0.500	0.259
Observations	570,193	570,193	570,193
Number of districts	480	480	490
R-squared	0.220	0.227	0.091

Note: Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is restricted to common support in Panels C and D. District, state-year, and interview month-year fixed effects are included in all regressions.

Table A.7: Effect of MGNREGA on the use of family planning methods for women below the age of 18

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post	0.031	0.021	0.009
	(0.019)	(0.013)	(0.014)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.090	0.050	0.040
SD dependent variable	0.286	0.219	0.195
Observations	14,716	14,716	14,716
Number of districts	459	459	459
R-square	0.186	0.137	0.148

Note: Robust standard errors in parentheses are clustered at the level of treatment (district). Dependent variables comprise women under 18 years of age. Controls at the individual and household level are included in every regression.

Table A.8: Effect of MGNREGA on selected use of modern contraceptives: Triple difference

	Permanent contraceptives	Reversible contraceptives
MGNREGA x Post x Age 35 years and older	-0.025	0.015^{**}
	(0.017)	(0.007)
MGNREGA x Post	0.014^{*}	0.002
	(0.007)	(0.005)
District FEs	Yes	Yes
State-year FEs	Yes	Yes
Interview month-year FEs	Yes	Yes
Mean dependent variable	0.380	0.103
SD dependent variable	0.485	0.304
Observations	570,193	570,193
Number of districts	480	480
R-square	0.286	0.102

Note: Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is restricted to common support and excludes current pregnant women. WLS estimator is used for all regressions. All dependent variables are binary (1/0). Controls at the individual and household level are included in every regression. The minimum age for working in the MGNREGA is 18. Permanent contraceptives include female and male sterilization. Reversible contraceptives include IUDs/Copper-t/Loop, oral pills, male and female condoms, and others. Married women 35 years and older represent a binary variable (1/0).

Table A.9: Effect of MGNREGA on selected use of modern contraceptives: Triple difference

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post x High share of contraceptive use	-0.039^{**}	-0.010	-0.029^{*}
	(0.018)	(0.014)	(0.016)
MGNREGA x Post	0.037^{**}	0.015	0.021
	(0.017)	(0.012)	(0.014)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.558	0.486	0.072
SD dependent variable	0.497	0.500	0.259
Observations	570,193	570,193	570,193
Number of districts	480	480	480
R-square	0.220	0.227	0.091

Note: Levels of significance: p$<0.01^{***}$, p$<0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is restricted to common support and excludes current pregnant women. WLS estimator is used for all regressions. All dependent variables are binary (1/0). Controls at the individual and household level are included in every regression. The high share of contraceptive use is a dummy variable, 1 for values above the average of all modern contraceptive use in a district and 0 for others.

Table A.10: Robustness check: Coarsened Exact Matching method

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post	0.020***	0.017***	0.003
	(0.008)	(0.006)	(0.005)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.583	0.508	0.075
SD dependent variable	0.493	0.500	0.263
Observations	450,442	450,442	450,442
Number of districts	536	536	536
R-squared	0.206	0.219	0.095

Note: Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). WLS estimator is used across all regressions. Controls at the individual and household level are included in every regression. The coarse variables used were age of women, literacy of women and spouses, religion, scheduled castes/tribes, number of children and wealth index. The match summary consists of: 225,420 matched on 242,257 observations for control and 225,420 matched on 388,895 for treatment.

Table A.11: Robustness check: Probit

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post	0.058**	0.041**	0.050
	(0.024)	(0.020)	(0.042)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.558	0.486	0.073
SD dependent variable	0.497	0.500	0.260
Observations	570,183	570,166	563,289
Number of districts	480	480	473

Note: This table reports probit regression estimates. IP weight is applied across all regressions. Sample is restricted to common support. Robust standard errors in parentheses are clustered at the level of treatment (district). Controls at the individual and household level are included in every regression. Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$.

Table A.12: Robustness check: Propensity score

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post	0.025^{***}	0.021^{***}	0.004
	(0.008)	(0.006)	(0.005)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.554	0.481	0.073
SD dependent variable	0.497	0.500	0.260
Observations	630,173	630,173	630,173
Number of districts	536	536	536
R-square	0.218	0.227	0.090

Note: Robust standard errors in parentheses are clustered at the level of treatment (district). Controls at the individual and household level are included in every regression. Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$.

Table A.13: Effect of MGNREGA on the use of family planning methods by household wealth index: Triple difference

	Any methods	Any modern methods	Any traditional methods
MGNREGA x Post x Poor	-0.007	-0.016	0.009
	(0.011)	(0.010)	(0.006)
MGNREGA x Post	0.019^{**}	0.019^{***}	0.0003
	(0.008)	(0.007)	(0.005)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.558	0.486	0.072
SD dependent variable	0.497	0.500	0.259
Observations	570,193	570,193	570,193
Number of districts	480	480	480
R-squared	0.223	0.229	0.091

Note: Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$. Robust standard errors in parentheses are clustered at the level of treatment (district). The sample is restricted to common support and excludes current pregnant women. WLS estimator is used across all regressions. All regressions include controls at the individual and household level. Poor is coded as 1 for low wealth and 0 if not. See note to Table 1.4 for other details.

Table A.14: District-level variables

Variable	Source
Total Population	2001 Census
Percent rural	2001 Census
Area (in square km)	2001 Census
Percent Scheduled Castes	2001 Census
Percent Scheduled Tribes	2001 Census
Percent Literate	2001 Census
Average monthly per capita consumption expenditure	2004/05 NSSEUS
Average casual wage (2004/05 prices)	2004/05 NSSEUS
Labor force participation rate	2004/05 NSSEUS
Female labor force participation rate	2004/05 NSSEUS
Rainfall (2004)	NCMRWF
Growing degree days (2004)	NCMRWF

Note: I use the socioeconomic high-resolution rural-urban geographic platform for India (SHRUG) [Asher et al., 2021] to construct 2001 census variables. NSSEUS refer to the National Sample Surveys on Employment and Unemployment Situation in India. NCMRWF refer to the National Centre for Medium Range Weather Forecasting [Rani et al., 2021]. I use growing season (June through September) in a given year to construct rainfall and growing degree days.

Table A.15: Alternative main regression results using population-weighted rain measures

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.027	-0.143***	-0.016	-0.046
	(0.050)	(0.042)	(0.062)	(0.052)
High SOC (%)	-0.011	-0.020	-0.008	-0.021
	(0.018)	(0.015)	(0.021)	(0.018)
High SOC $\times$ Fraction of shocks	-0.017	0.102*	-0.073	0.038
	(0.072)	(0.058)	(0.089)	(0.071)
DHS controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	-1.558	-0.991	-1.573	-1.059
SD dependent var.	1.681	1.381	1.667	1.366
Observations	169,904	169,904	102,296	102,296
R-square	0.148	0.090	0.144	0.079

Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$, $p < 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 50th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time.

Table A.16: Means, standard deviation and Pearson correlation matrix for soil attributes (N = 169,897)

	Means	SD	WHZ	SOC	Clay	Sand	Silt	EVI	Slope
WHZ	-0.99	1.38	1.00						
SOC	0.94	0.67	0.12^{a}	1.00					
Clay	32.44	5.33	-0.09^{a}	-0.08^{a}	1.00				
Sand	38.18	5.58	0.02^{a}	0.02^{a}	-0.57^{a}	1.00			
Silt	29.39	5.08	0.07^{a}	0.06^{a}	-0.43^{a}	-0.50^{a}	1.00		
EVI	2927.33	702.22	0.10^{a}	0.38^{a}	0.02^{a}	-0.15^{a}	0.14^{a}	1.00	
Slope	0.29	111.22	0.00	-0.25^{a}	0.00	0.00	0.00	0.21^{a}	1.00

Note: $^{a}p < .01$. EVI: Enhanced Vegetation Index for 2015.

Table A.17: Robustness check: confounding variables included as controls

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.056	-0.166***	0.070	-0.152***
	(0.050)	(0.042)	(0.063)	(0.053)
High SOC (%)	-0.011	-0.023	-0.005	-0.016
	(0.018)	(0.016)	(0.021)	(0.018)
High SOC × Fraction of shocks	-0.022	0.135**	-0.089	0.098
	(0.072)	(0.059)	(0.090)	(0.072)
DHS controls	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	-1.558	-0.991	-1.572	-1.061
SD dependent var.	1.681	1.381	1.667	1.369
Observations	169,897	169,897	102,296	102,296
R-square	0.148	0.090	0.142	0.080

Levels of significance: p< 0.01***, p< 0.05**, p< 0.1*. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 50th percentile. DHS controls include child, mother, and household level characteristics. Other controls include confounding variables such as soil texture, slope, and vegetation.

Table A.18: Sensitivity test for various thresholds: High soil organic carbon content above 25 percentile.

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.153**	-0.233***	0.155**	-0.214***
	(0.063)	(0.055)	(0.067)	(0.059)
High SOC (%)	0.012	-0.026	0.016	-0.017
	(0.022)	(0.018)	(0.027)	(0.022)
High SOC × Fraction of shocks	-0.147**	0.186***	-0.233***	0.151**
	(0.072)	(0.061)	(0.086)	(0.076)
DHS controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	-1.558	-0.991	-1.573	-1.059
SD dependent var.	1.681	1.381	1.667	1.366
Observations	169,904	169,904	80,253	80,253
R-square	0.148	0.090	0.145	0.094

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 25th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. The match summary consists of: the number of balanced matched observations is 40129 for treatment and control; and the unmatched observation is 2354 out of 42483 for control and 87292 out of 127421 for treatment.

Table A.19: Sensitivity test for various thresholds: High soil organic carbon content above 75 percentile.

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.048	-0.114***	0.122	-0.091
	(0.042)	(0.037)	(0.093)	(0.080)
High SOC (%)	-0.015	-0.022	-0.022	-0.000
	(0.028)	(0.023)	(0.034)	(0.029)
High SOC × Fraction of shocks	-0.003	0.066	-0.122	-0.020
	(0.085)	(0.072)	(0.124)	(0.106)
DHS controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	-1.558	-0.991	-1.573	-1.059
SD dependent var.	1.681	1.381	1.667	1.366
Observations	169,904	169,904	45,498	45,498
R-square	0.148	0.090	0.145	0.094

Levels of significance: p$<0.01^{***}$, p$<0.05^{**}$, p$<0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 75th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. The match summary consists of: the number of balanced matched observations is 22749 for treatment and control; and the unmatched observation is 104676 out of 127425 for control and 19730 out of 42479 for treatment.

Table A.20: Sensitivity test for different DHS cluster level: 20 km

	(1) Full	(2) Full	(3) Full	(4) Matched
Fraction of shocks	-0.241***	-0.242***	-0.260***	-0.229***
	(0.054)	(0.054)	(0.055)	(0.060)
High SOC (%)	-0.017	-0.023	-0.023	-0.008
	(0.018)	(0.018)	(0.018)	(0.022)
High SOC $\times$ Fraction of shocks	0.129**	0.154**	0.163***	0.109
	(0.061)	(0.061)	(0.061)	(0.076)
Marginal effects	-0.144***	-0.127***	-0.137***	-0.174***
	(0.034)	(0.033)	(0.034)	(0.047)
Mean dependent variable		-0.991		-1.075
Average years of exposure		0.133		0.150
DHS controls	No	Yes	Yes	Yes
Weather controls	No	No	Yes	Yes
Observations	169,904	169,904	169,904	80,254
Adjusted R^2	0.067	0.086	0.086	0.068

Levels of significance: p<0.01***, p<0.05**, p<0.1*. Robust standard errors in parentheses are clustered at the DHS cluster level. The high SOC level is fixed above the 25th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. All regressions include district and month-birth year specific fixed effects. The matching summary includes: 40,129 matched out of 42,483 observations for control and 40,129 matched out of 127,421 for treated.

Table A.21: Including dry and rainy seasons as an additional variable in the matching algorithm.

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.058	-0.161***	0.030	-0.102*
	(0.050)	(0.042)	(0.063)	(0.053)
High SOC (%)	-0.011	-0.023	-0.011	-0.016
	(0.018)	(0.015)	(0.021)	(0.018)
High SOC × Fraction of shocks	-0.023	0.136**	-0.072	0.036
	(0.072)	(0.059)	(0.091)	(0.072)
DHS controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	-1.558	-0.991	-1.580	-1.065
SD dependent var.	1.681	1.381	1.665	1.366
Observations	169,904	169,904	97,441	97,441
R-square	0.148	0.090	0.147	0.080

Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$, $p < 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 50th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. The match summary consists of: the number of balanced matched observations is 48721 for treatment and control; and the unmatched observation is 36229 out of 84950 for control and 36233 out of 84954 for treatment.

Table A.22: Sensitivity check for different SOC thresholds

	Child wasting at various SOC thresholds.		
	25th	50th	75th
Fraction of shocks	1.482***	1.309***	1.290***
	(0.131)	(0.088)	(0.076)
High SOC (%)	1.008	1.053**	1.065
	(0.032)	(0.027)	(0.041)
High SOC $\times$ Fraction of shocks	0.764***	0.855	0.750**
	(0.075)	(0.082)	(0.093)
DHS controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Mean dependent. var.	0.209	0.209	0.209
SD dependent var.	0.406	0.406	0.406
Observations	169,879	169,879	169,879

Levels of significance: p$< 0.01^{***}$, p$< 0.05^{**}$, p$< 0.1^{*}$. Odds ratios are reported. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time.

Table A.23: Moderating impacts of high SOC on crop yields

	Cereal
SOC (%)	0.018
	(0.020)
Rainfall decile 1	-0.129***
	(0.029)
Rainfall decile 1 x SOC (%)	0.038**
	(0.018)
Rainfall decile 2	-0.051*
	(0.027)
Rainfall decile 2 x SOC (%)	0.010
	(0.020)
Rainfall decile 3	-0.016
	(0.024)
Rainfall decile 3 x SOC (%)	0.004
	(0.019)
Rainfall decile 7	-0.049
	(0.031)
Rainfall decile 7 x SOC (%)	0.060***
	(0.023)
Rainfall decile 8	0.049**
	(0.021)
Rainfall decile 8 x SOC (%)	-0.001
	(0.020)
Rainfall decile 9	0.071**
	(0.028)
Rainfall decile 9 x SOC (%)	-0.015
	(0.026)
Rainfall decile 10	0.084***
	(0.025)
Rainfall decile 10 x SOC (%)	-0.001
	(0.019)
Observations	7091
Adjusted R^2	0.460

Levels of significance: p$<0.01^{***}$, p$<0.05^{**}$, p$<0.1^{*}$. Robust standard errors in parentheses are clustered at the district level. The 5th decile is selected as reference. For reasons of brevity, results for decile 4 and 6 are not presented.

Table A.24: Survey households by type of disability.

At least one type of disability	Households	Percent
Rare disability	5,658	4.8%
Mental	13,267	11.2%
Speech	9,215	7.8%
Visual	10,915	9.2%
Hearing	10,383	8.8%
Locomotor	50,874	43.1%
Without any disability	17,840	15.1%
Total	**118,152**	**100%**

Source: National Survey of Persons with Disabilities: 76th round (2018).

Table A.25: Selective mortality and fertility test

	Cohort size	Female to male
In-utero shock	0.466^{***}	-0.006
	(0.093)	(0.013)
District FEs	Yes	Yes
Birth year FEs	Yes	Yes
Mean dependent var.	11.755	1.154
Observations	40,787	37,772
Adjusted R^2	0.694	0.033

Levels of significance: $p< 0.05^{**}$. Robust standard errors in parentheses clustered at the district level. Each column presents results from a separate regression.

Table A.26: Robustness check: Including people with multiple disabilities

	Any disability
Drought	0.010***
	(0.004)
District FEs	Yes
State-Birth year FEs	Yes
Mean dependent var.	0.083
Observations	497,304
R-squared	0.042

Levels of significance: p< 0.01***, p< 0.05**, p< 0.1*. Robust standard errors in parentheses are clustered on year of birth and at the district level. "Any disability" includes all types of physical and mental disabilities, as well as persons with multiple disabilities. Control variables include gender, age, education level, household type, social group, household size and land size.

Table A.27: Robustness check: Including extreme rainfall as control

	(1) Any disability	(2) Visual disability	(3) Hearing disability	(4) Speech disability	(5) Locomotor disability	(6) Cognitive impairment
Drought	0.009***	-0.000	0.000	0.001	0.005**	0.004**
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Extreme precipitation	0.001	0.002**	-0.000	-0.002**	0.004	-0.000
	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
State-Birth year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent var.	0.091	0.009	0.007	0.003	0.049	0.016
Observations	453,418	415,745	414,717	413,293	433,395	418,601
R-squared	0.302	0.596	0.553	0.172	0.336	0.038

Levels of significance: p< 0.01***, p< 0.05**, p< 0.1*. Robust standard errors in parentheses are clustered on year of birth and at the district level. I define extreme precipitation as annual precipitation in any given year above the 80th percentile of historical district precipitation. Each column presents results from a separate regression. The sample includes individuals with a disability at birth. "Any disability" includes all types of physical and mental disability. Columns 2 to 7 exclude all other types of disabled people.

Table A.28: Robustness checks at different base level

	Any disability
Drought	-0.001
	(0.004)
Tropical wet	-0.010***
	(0.002)
Arid	-0.007*
	(0.004)
Semi-arid	0.004**
	(0.002)
Humid sub-tropical	-0.004*
	(0.002)
Mountain	-0.004
	(0.009)
Drought x Tropical wet	0.021**
	(0.008)
Drought x Arid	0.010
	(0.014)
Drought x Semi-arid	0.006
	(0.007)
Drought x Humid sub-tropical	0.004
	(0.005)
Drought x Mountain	0.009
	(0.023)
State FEs	Yes
Birth year FEs	Yes
P-val: Drought + Drought x Climate zone	0.049
Mean dependent var.	0.091
Observations	453,429
R-squared	0.295

Levels of significance: $p < 0.01^{***}$, $p < 0.05^{**}$, $p < 0.1^{*}$. Robust standard errors in parentheses are clustered on year of birth and at the district level. Tropical wet and dry is a reference climatic zone. Control variables include gender indicator, onset of disability in old age, education level, household type (rural/urban), social group, household size and land area.