The Heat Trap: Climate, Fetal Origins, and the Compression of Intergenerational Mobility*

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Abstract

Does climate compress intergenerational mobility? We show that it does. Linking child-father matched records from a nationally representative household survey to high-resolution historical temperature data across districts and five decades of birth cohorts, we find that a one degree Celsius increase in prenatal growing season temperature reduces the probability of upward educational mobility by 18.5% and occupational mobility by 10.7%. The effect operates through two reinforcing channels: biological damage to the fetal endowment, transmitted via deteriorating maternal health, and resource depletion that constrains compensatory parental investment. A life-cycle falsification confirms that vulnerability is confined to the in-utero and early childhood window. Credit market depth substantially moderates the trap.

Keywords: Intergenerational Mobility, Human Capital, Heat, Fetal Origins, Climate

JEL Codes: I24, J62, O12, O15, Q54

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1 Introduction

A large literature documents that rising temperatures depress productivity, reduces labor supply, and erodes household income (Hsiang, 2016; Schlenker and Roberts, 2009; Somanathan et al., 2021; Liu, Shamdasani, and Taraz, 2023; Shah and Steinberg, 2017). A separate literature establishes that prenatal environmental stress leave persistent biological imprints on human capital (Almond, 2006; Almond and Currie, 2011; Currie, 2011; Adhvaryu, Fenske, and Nyshadham, 2019; Adhvaryu et al., 2024). These two channels are not independent: in economies where consumption and income are climate-sensitive and credit markets are thin, the same temperature shock that damages fetal endowments simultaneously depletes household resources that might otherwise compensate for them. Whether this compounding of biological and economic forces is large enough to alter intergenerational mobility is an open question in contexts where prenatal heat exposure and shallow credit markets coexist.

We call this mechanism the *Heat Trap*: the compounding of a biological endowment tax, inflicted in utero by extreme thermal stress on the developing fetus, with a simultaneous depletion of health and the household resources that could otherwise compensate for it. The two channels reinforce each other in a manner formalized by the dynamic complementarity framework of Cunha and Heckman (2007): a child born with impaired neural and physiological endowments receives lower marginal returns from every dollar of parental investment in schooling, so the income shock that accompanies heat, through crop losses, labor productivity declines, and distress borrowing, lands on a family that is already less equipped to convert spending into human capital. The result is not merely a contemporaneous productivity shock but a structural compression of the ceiling on intergenerational upward mobility, one that persists visibly in the data for decades after the birth year in question.

We construct a matched child-father dataset from the India Human Development Survey (IHDS) 2011-12, a nationally representative survey of approximately 42,000 households covering 371 districts and all major states and union territories. For 129,351 adult respondents, born between 1950 and 1996 and aged 15–62 at the time of the survey, we observe completed education, current occupation, and the corresponding educational and occupational outcomes of their fathers. We map each individual to the district in which she was born, and merge in high-resolution gridded temperature and precipitation data from the University of Delaware's Terrestrial Air Temperature and Precipitation dataset (Matsuura and Willmott, 2018a,b), which provides monthly coverage at a 0.5-degree spatial resolution from 1900 onward. Our primary exposure variable is the ten-year average growing-season temperature (June through December) prevailing in the individual's district during the year prior to birth, capturing the decadal climate into which the fetus was gestated, rather than high-frequency weather fluctuations that may partly reflect short-run household adaptation.

Following Stainier, Shah, and Barreca (2026), and Liu, Shamdasani, and Taraz (2023), our identification rests on within-district variation in decadal temperature across birth cohorts, con-

ditional on district fixed effects, birth-year fixed effects, birth-month fixed effects, state-specific linear trends in birth year, and a rich vector of individual and household controls. District fixed effects absorb all time-invariant geography, agro-climatic zones, and institutional heritage. State-specific trends flexibly allow for divergent trajectories in educational expansion (Khanna, 2023) and structural transformation (Lamba and Subramanian, 2020) across India's heterogeneous states. The maintained assumption, that residual year-to-year fluctuations in a district's decadal temperature are uncorrelated with unobserved determinants of intergenerational mobility, conditional on this set of controls, is supported by a battery of validation exercises including selective survival, cross-district spillovers up to 500 kilometers, two-way clustering by district and birth year, logistic specifications, weighted regressions, alternative definitions of weather variables, nonparametric estimation with flexible temperature bins, quadratic trends in birth year, and isolating temperature from moisture-driven income shocks.[1]

Our core finding is that a one-degree Celsius increase in in-utero growing-season temperature reduces the probability that a child surpasses her father's educational attainment by an 18% decline relative to the baseline mobility rate of 56.6 percent. Expressed in distribution terms, the same temperature shock pushes the child 3.3 percentiles down the national education rank. The effect is especially stark at the bottom of the parental distribution: children born to fathers in the lowest quartile of educational attainment become increasingly less likely to reach the upper half of the child's distribution. These magnitudes are robust to the full set of specification checks described above; the coefficient on growing-season temperature is statistically indistinguishable across all robustness tables, while the coefficient on growing-season precipitation is uniformly insignificant across all specifications, establishing that the Heat Trap is a thermal phenomenon distinct from the rainfall shocks that dominate the existing Indian climate literature (Jayachandran, 2006; Shah and Steinberg, 2017).

The mobility penalty extends from educational attainment into occupational structure. A one-degree increase in in-utero temperature reduces the probability of intergenerational occupational mobility, derived from Alesina et al. (2021), by 4.6 percentage points, makes an individual less likely to escape agriculture entirely, and reduces the probability of transitioning into a high-skill occupation. Absolute schooling outcomes mirror these mobility patterns: the probability of completing primary school falls, and elementary school and university completion fall even more. While on the other hand, the probability of ending up in casual wage labor, the most economically precarious occupational status rises statistically significantly.

Our contribution also lies in decomposing the Heat Trap into its two constituent channels using complementary data sources. For the *resource depletion channel*, we use the household module of the IHDS to show that a one-degree increase in average decadal growing-season temperature raises the probability of a major household loss or accident, and increases the probability of

[1] Additionally, leveraging the plausibly exogenous variation in in-utero temperature exposure (Maccini and Yang, 2009), we implement causal mediation analysis to quantify the biological and resource channels, and use instrumental-variable specifications in which prenatal temperature instruments predicted adult morbidity and household economic distress.

taking a loan for medical expenditure. Medical debt, in the absence of universal health insurance, functions as a binding liquidity constraint that diverts resources from children's education into debt service, a mechanism formalized by Jayachandran (2006) in the context of rainfall shocks. We also document a statistically significant increase in the probability of job loss per additional degree, connecting our findings to the heat-productivity literature (Somanathan et al., 2021).

For the *biological endowment channel*, we draw on the NFHS 2015-16 to establish that heat exposure during pregnancy triggers a systemic physiological decline in mothers: a one-degree increase in growing-season temperature raises Metabolic Syndrome Index (MSI), driven by significant increases in high blood pressure, diabetes, heart disease, and obesity. These maternal health deficits represent a degraded in-utero environment that directly impairs fetal development. Children born into this environment are smaller in size and are underweight, and exhibit a higher probability of anemia, longer delays in breastfeeding, and higher incidence of early-childhood diarrhea, markers of immunological fragility and nutritional deficit that reduce the cognitive returns to subsequent schooling investments. A mediation analysis using predicted adult morbidity from the IHDS individual module as an intermediate outcome confirms that the majority effect of growing-season temperature on intergenerational educational mobility passes through the health channel: when predicted major morbidity is included, the coefficient on temperature loses statistical significance while a one-standard-deviation increase in predicted morbidity reduces the probability of upward mobility by 22.5 percentage points.

A falsification exercise on the timing of exposure across the life cycle provides an evidence for the biological interpretation. Estimating the effect of temperature at each year of exposure from fifteen years before birth to fifteen years after, we document an inverted-U pattern of vulnerability centered precisely on the in-utero and early-childhood window: the negative effect materializes in the pre-conception year, peaks in utero and through age three, and attenuates monotonically toward zero by adolescence. Coefficients for distant pre-birth years are precise nulls, ruling out the alternative that temperature proxies for a persistent regional poverty gradient. If heat were simply capturing aggregate regional underdevelopment, its effect should be constant across the life cycle; the sharply delimited biological window identifies it, instead, as a developmental scar inflicted during a critical period of neurological plasticity.

Three heterogeneity results deepen the interpretation. First, the educational mobility penalty is, counterintuitively, larger for children of fathers above the median of the educational distribution, those with more education to lose from rising temperatures, suggesting that the Heat Trap does not merely prevent the poor from rising but actively pulls the middle class downward, potentially eroding the gains of prior generations. Second, the penalty is statistically indistinguishable for children of agricultural and non-agricultural fathers, establishing that the biological channel operates independently of sectoral income shocks and is not confined to families directly exposed to agricultural volatility. Third, and most consequential for policy, the mobility penalty is nearly three times larger in districts with below-median bank credit per capita in 1961: where historical credit markets were shallow, the Heat Trap tightens, because families cannot borrow

against future income to preserve investments in children's human capital when contemporaneous income falls..

This paper sits at the intersection of three literatures and advances each. We build on the intergenerational mobility framework of Chetty et al. (2014), Alesina et al. (2021), and Asher, Novosad, and Rafkin (2024) by demonstrating that climate volatility is a quantitatively important and previously unacknowledged determinant of where families land in the intergenerational distribution. We extend the fetal origins literature (Almond, 2006; Almond and Currie, 2011; Currie, 2011) by tracing the in-utero biological tax on the intergenerational rank of the individual relative to her father, a measure that integrates the full life-cycle consequences of early-life damage. And we advance the literature on climate and economic development in India (Jayachandran, 2006; Shah and Steinberg, 2017; Liu, Shamdasani, and Taraz, 2023; Stainier, Shah, and Barreca, 2026; Somanathan et al., 2021) by demonstrating that the costs of heat are not contemporaneous and recoverable but are partially encoded in the next generation's human capital, compounding across cohorts in a manner that aggregate productivity regressions cannot detect.

Approximately 12 percent of the Indian population currently experiences growing-season temperatures above the 27°C threshold, and under plausible climate trajectories this share will rise substantially over the coming decades (Schlenker and Roberts, 2009). Our estimates imply that this exposure is not merely a productivity tax on current workers but a forward-looking tax on the children they will raise, operating through channels, including, maternal metabolic health, infant immunological development, and household liquidity constraints, that conventional climate-economy models omit entirely. The Heat Trap, in this sense, is a mechanism through which the physical climate becomes self-reinforcing social geography: hotter districts today produce children with lower human capital tomorrow, narrowing the base from which economic development can proceed and widening the gap between India's climate-favored and climate-exposed regions across generations.

Section 3 describes the data sources and presents descriptive statistics on mobility patterns and climate variation. Section 4 lays out the empirical strategy and identification assumptions. Section 5 presents the core results on educational and occupational mobility, followed by the mechanism analysis and the life-cycle exposure falsification. Section 6 explores heterogeneous effects by parental education, parental occupation, gender, urbanization, and historical credit access. Section 7 reports the robustness and sensitivity checks. Section 8 concludes.

2 Conceptual Framework and Related Literature

Our study intersects and extends three primary strands of economic inquiry: the determinants of intergenerational mobility, the "fetal origins" of human capital, and the long-run economic consequences of climate change. We bridge these literatures by proposing a unified conceptual model, the *Heat Trap*, where prenatal environmental shocks serve as a structural barrier to upward mobility.

2.1 Conceptual Framework: The Heat Trap

Figure 1 delineates the theoretical channels through which prenatal temperature exposure governs intergenerational trajectories. We conceptualize the impact of heat as operating through two reinforcing pathways: a biological channel and a resource-depletion channel.

First, the *biological channel* is rooted in the fetal origins hypothesis (Barker, 1990; Adhvaryu et al., 2024). Extreme heat during the prenatal growing season induces physiological stress and nutritional deficits, which degrade the child's initial biological endowment. Following the technology of skill formation developed by Cunha and Heckman (2007), these early-life impacts are subject to dynamic complementarity: a lower initial endowment reduces the marginal productivity of all subsequent investments, creating a permanent drag on the child's human capital accumulation.

Second, the *resource-depletion channel* operates through the household budget constraint. In an agrarian-dependent economy like India, high temperatures during the growing season depress yields (Schlenker and Roberts, 2009; Liu, Shamdasani, and Taraz, 2023) and rural wages (Jayachandran, 2006), leading to immediate income shocks. For credit-constrained households, this loss of income curtails the ability of parents to make compensatory investments to offset the initial biological damage. As illustrated in Figure 1, these dual shocks culminate in a compression of intergenerational mobility, where the child's ultimate educational and occupational rank is systematically decoupled from their potential, effectively trapping the household in a cycle of low-equilibrium human capital.

2.2 Related Literature

A robust literature documents the persistence of economic status across generations, primarily focusing on rank-based metrics (Chetty et al., 2014). While mobility in the United States exhibits sharp geographic variation, recent evidence from developing economies highlights the roles of historical and institutional frictions. Alesina et al. (2021) find low absolute upward mobility in Africa, while Asher, Novosad, and Rafkin (2024) provide the first comprehensive estimates for India, documenting significant stratification by caste and geography despite rising aggregate mobility. We build on the measurement frameworks of Alesina et al. (2021) and Asher, Novosad, and Rafkin (2024) but shift the focus toward an exogenous environmental determinant. We ask whether prenatal climatic conditions can systematically lower the ceiling on upward mobility, providing a structural explanation for the geographic heterogeneity observed in the prior literature.

Our work contributes to the literature on the long-term effects of in-utero exposure to exogenous shocks. Seminal work by Almond (2006) and Almond and Currie (2011) established that prenatal insults lead to significant adult penalties in health and earnings. In the context of climate, Maccini and Yang (2009), Shah and Steinberg (2017) and Garg, Jagnani, and Taraz (2020) demonstrate that rainfall and temperature shocks in early life shape adult health and contemporaneous cognitive ability in Indonesia and India, respectively. We advance this literature by tracing these effects beyond individual outcomes to the *intergenerational* level. By analyzing the

child's rank relative to the father, we quantify how climatic shocks at birth erode the stock of intergenerational upward mobility, rather than merely depressing the level of human capital.

Finally, we contribute to the growing body of work on the productivity costs of heat. High temperatures are known to reduce agricultural output (Schlenker and Roberts, 2009), depress labor productivity (Somanathan et al., 2021), and disrupt household consumption smoothing (Jayachandran, 2006; Liu, Shamdasani, and Taraz, 2023). While these papers focus on contemporaneous or short-run economic adjustments, we provide a multi-generational perspective. Our findings suggest that the aggregate productivity costs of heat, well-documented in the macro-climate literature (Hsiang, 2016), accumulate into a life-cycle trap that limits occupational re-allocation and educational attainment for decades after the initial exposure.

3 Data and Descriptive Statistics

Our analysis combines individual-level data on intergenerational mobility with high-resolution historical weather data. We describe each data source and present summary statistics on mobility patterns and climate variation.

3.1 India Human Development Survey

Our primary data on intergenerational mobility come from the India Human Development Survey (IHDS), a nationally representative household survey conducted in 2011-2012. The IHDS collects detailed information on educational attainment, occupation, income, and demographics for all household members, as well as retrospective information on parents' education and occupation. The survey covers approximately 42,000 households across all Indian states and union territories, providing comprehensive coverage of the country's socioeconomic diversity.

Following Asher, Novosad, and Rafkin (2024) and Ahsan et al. (2025), we transform the IHDS cross-sectional data into a child-parent matched dataset. For each adult respondent aged 15-70 years, we record their educational attainment and current occupation, as well as the education and occupation of their fathers. We restrict our analysis to individuals born after 1950 to avoid effects of the partition of India in 1947 on education levels (Bharadwaj, Khwaja, and Mian, 2015; Kyle Emerick, 2025), leaving us with a sample of age group 15-62 years.

We code the information available on completed years of education into seven categories: no education, below primary, primary, elementary school, secondary, higher secondary, and graduate and above. Following Alesina et al. (2021), we construct a binary indicator of upward *Intergenerational Educational Mobility*: $IEM_i = \mathbb{1}\{E_i > E_f\}$ which indicates the probability of child i attaining strictly higher education level E_i than their father f. This measure captures absolute upward mobility: whether children achieve more education than their parents in an absolute sense, regardless of their position in the overall education distribution.

To study upward movement in education distribution, we assign ranks to children and their fathers in their respective education distributions (Asher, Novosad, and Rafkin, 2024). We use

the *Child's Education Rank* as our second outcome, for which we particularly account the father's education rank (Chetty et al., 2014). In resonance with Asher, Novosad, and Rafkin (2024) and Van der Weide et al. (2024), we study the probability of *Bottom Quartile Upper-Half Mobility*, $Q1UH = \mathbb{P}\{R_i > 50 \mid R_f \in [0, 25]\}$ to study the likelihood that children born to fathers from the bottom quartile of the fathers distribution, reach the upper half of the children distribution.[2]

Occupations are classified into three broad categories reflecting skill intensity and economic status: agriculture (crop cultivation and animal husbandry), blue collar (manual labor including construction, manufacturing, and services), and white collar (professional, technical, clerical, and managerial positions) (Hnatkovska, Lahiri, and Paul, 2013). For O_i , $O_f \in \{1, 2, 3\}$ denoting Agricultural, Blue collar and White collar Occupations respectively, we study upward *Intergenerational Occupational Mobility* using $IOM_i = \mathbb{1}\{O_i > O_f\}$. This hierarchical ranking of occupations follows the approach of Acciari, Polo, and Violante (2022) and provides a transparent measure of absolute upward mobility that captures whether individuals achieve superior occupational outcomes relative to their parents. We also create a binary indicator of *Mobility towards Non-Agricultural Occupations* that equals one for an individual working in a non-agricultural occupation, whose father is in an agricultural occupation, and zero otherwise.

Our third metric of upward occupational mobility is based on human capital intensity of occupations. Following Brahma (2025) and Ahsan and Chatterjee (2017), we collapse the detailed occupation codes (as per the National Classification of Occupations 1968 list) into seven broad groups (Hnatkovska, Lahiri, and Paul, 2013), and compute the educational intensity for each of them as: $OS_o = \sum_{i=1}^{n_o} \left(\frac{\omega_i}{\sum_{i=1}^{n_o} \omega_i} \right) E_i$, where o indexes occupations, n_o is the number of individuals in each occupation, $E_i \in \{0, 2, 5, 8, 10, 12, 14\}$ denotes the education level of each individual (as per the National Sample Surveys of India), and ω_i is the sampling weight. We define an individual to be upward mobile, if he/she is engaged in an occupation that has a higher human capital score than that of their father.

The IHDS records district of residence for each household, which we use to merge individual records with historical weather data. The survey covers 589 districts across India, providing substantial geographic variation for identifying the effects of climate exposure. We assign each individual to the district in which they currently reside, under the assumption that most individuals remain in or near their birth location. While some migration occurs, internal migration rates in India are relatively low, particularly for the cohorts in our sample, and any measurement error from migration is likely to attenuate our estimates toward zero, implying that our results represent lower bounds on the true effects.

[2]Rank-based mobility metrics are grounded in the rank-based intergenerational mobility framework pioneered by Chetty et al. (2014) and Solon (1999) and formalized using the conditional expectation function (CEF) of a child's educational rank given the parent's rank, thereby capturing intergenerational persistence. Defining outcomes in terms of ranks ensures that estimated mobility is invariant to changes in the level or dispersion of education across cohorts, thereby separating intergenerational mobility from secular trends in educational expansion or shifts in inequality, which is crucial for the Indian context (Asher, Novosad, and Rafkin, 2024).

3.2 Weather Data

We obtain gridded monthly temperature and precipitation data from the Terrestrial Air Temperature and Precipitation: Monthly Time Series datasets, maintained by the University of Delaware, which provides global coverage at a 0.5-degree spatial resolution from 1900 to 2017 (Matsuura and Willmott, 2018a,b). These data are constructed from weather station observations using spatial interpolation methods that account for elevation and local topography. The dataset has been widely used in climate research and provides reliable historical weather information for India.

For each district-year, we calculate average temperature and total precipitation for two seasons: the growing season (June through December) and the non-growing season (March through May) (Stainier, Shah, and Barreca, 2026). The growing season corresponds to the kharif cropping period, when most agricultural production occurs and when prenatal temperature exposure is most likely to affect fetal development through both biological and economic channels. To each individual in the household survey, we assign them the weather conditions in their district of residence for the year before their birth, capturing in-utero exposure to average decadal temperature and precipitation levels.[3] While these measures capture specific climatic shocks, they remain limited summaries of a more complex joint probability distribution of atmospheric and oceanic conditions (Hsiang, 2016).

3.3 National Family Health Survey

To investigate mechanisms related to maternal and child health, we use data from the National Family Health Survey (NFHS) conducted in 2015-2016. The NFHS is a large-scale, nationally representative survey that collects comprehensive health information for women of reproductive age and children under five. Importantly, the NFHS includes biomarkers measured by trained health workers, including hemoglobin levels, blood pressure, and anthropometric measures. These objective health measures allow us to examine biological pathways linking temperature exposure to human capital formation.

To study effects on maternal health, we use the responses to whether a mother was diagnosed by a doctor with *High Blood pressure*, *Diabetes*, *Heart Disease*, and *Asthma*, and construct binary indicators to examine them. Considering the low frequency of these diseases and addressing concerns about multiple hypothesis testing, we construct a *Metabolic Syndrome Index* (MSI), by averaging standardized z-scores of high blood pressure, diabetes, heart disease, and obesity (Hoynes, Schanzenbach, and Almond, 2016; Sekhri and Shastry, 2024). Following World Health Organization (2025), we use the variable Body Mass Index (BMI) available in the data to define a binary indicator for *Obesity* as a BMI ≥ 30 kg/m^2 (Sekhri and Shastry, 2024; Singh et al., 2025). We exclude all pregnant women and those smoking cigarettes from the sample (Dasgupta, Majid, and Orman, 2023), although our results are not driven by this restriction.

[3]Following Stainier, Shah, and Barreca (2026) and Shah and Steinberg (2017), we construct two alternate measures of precipitation, "rainfall shocks" and "wet and dry" shocks, for each district-season-year, to decouple temperature from rainfall variation. We discuss them in Section 7 in detail.

We also analyze a range of child health outcomes, moving from preterm birth to post-birth and development indicators. We first examine *Size of the child at Birth*, a binary indicator equal to one if the child was of normal or large size at birth, and zero for small size. Second, as defined by World Health Organization (2022), we construct *Low Birth Weight*, a binary indicator equal to one if the child had weight at birth less than 2500 grams, and zero otherwise. We then move to post-birth measures: *Delay in Breastfeeding*, a categorical variable giving the time when the child was put into breastfeeding, ranging from immediately to days; and *Diarrhea*, a binary outcome equal to one if the child experienced diarrhea recently, and zero otherwise. Next, we follow the guidelines on child growth standards outlined by World Health Organization (2006), and construct child malnutrition binary indicators based on z-scores available in the survey. These include: *Stunting*, defined as a height-for-age (HAZ) score of less than -2 standard deviations; *Wasting*, defined as a weight-for-height (WHZ) score of less than -2 standard deviations; and *Underweight*, defined as a weight-for-age (WAZ) score of less than -2 standard deviations. We also examine if the child has anemia, using a binary indicator *Severe Anemia*, equal to one if the hemoglobin (Hg) level of the child is below 80 g/L, and zero otherwise, based on WHO guidelines (USAID, 2017). We exclude missing values and outliers in hemoglobin ($Hg \in (40, 180)$).

We link these health outcomes to in-utero exposure of the child, allowing us to trace the causal chain from environmental exposure to health deficits to mobility outcomes, while analyzing the effects on mother's health from exposure during her pregnancy. The regression specifications for these health outcomes account for the age of mother (and child), and include fixed effects for her education levels, along with wealth quintiles, urban residence, religion and social group of the household, besides the standard vector of state fixed effects, (respective) birth year and birth month fixed effects, and state-specific linear trends in birth year. We also account for the number of years, the mother has stayed in the current place of residence, to address issues regarding migration (Dasgupta, Majid, and Orman, 2023).

3.4 Household

In line with Stainier, Shah, and Barreca (2026) and Liu, Shamdasani, and Taraz (2023), we provide contemporary evidence on household reported losses using information from the Household module of the IHDS 2011-12 survey. We define binary indicators for loss due to major illness or accidents; drought, flood or fire related loss; loss of job; and other economic loss. Considering issues of low frequency of these outcomes and multiple hypothesis testing, we construct a Household Loss index by averaging standardized z-scores of the four binary indicators (Hoynes, Schanzenbach, and Almond, 2016). We also assess whether the household availed a loan for medical expenditure.

Since these are household-related outcomes, we link them with average decadal temperature and precipitation for the year ending 2010, while accounting for a vector of household demographic characteristics (age and education of household head, land, nonfarm business, and assets ownership, outstanding loan in preceding five years, poverty status, urban residence, and fixed

effects for income source, caste and religion), and regional zone fixed effects.

3.5 Descriptive Statistics

We present detailed summary statistics for our analysis sample in Table 1. Panel A highlights a notable difference in human capital: while fathers in our sample attained only 3.83 years of education on average, their children achieved 6.40 years, with 57% of the sample exhibiting upward educational mobility (IEM). This relatively low mobility rate (compared to 67-70% in the United States (Chetty et al., 2014)) reflects the strong persistence of educational attainment across generations in India, also found by Asher, Novosad, and Rafkin (2024). Despite this progress, occupational"stickiness" remains evident; while 62% of fathers were engaged in agriculture, 30% of children remain in the primary sector, and only 14% have transitioned into white-collar roles.

The demographic characteristics of our sample reflect India's diversity. The mean age of respondents is 34.16 years, implying that most were born in the 1970s and experienced childhood during a period of moderate economic growth and gradual expansion of educational access. Approximately 51% of the sample is female, close to the population average. Mean years of formal child education is 6.4 years, with substantial variation across individuals and cohorts. This reflects the rapid expansion of educational access in India over the latter half of the twentieth century, with younger cohorts achieving substantially higher educational attainment than older cohorts.

Panel D establishes the identifying variation in our weather exposure. Average growing season temperature in our sample is 25.26°C , with substantial variation across districts and years. The standard deviation of 2.41°C indicates considerable spatial and temporal variation in temperature exposure. Approximately 12% of observations experience temperatures above 27°C during the growing season, a threshold associated with reduced agricultural yields and increased health risks in the medical literature (Schlenker and Roberts, 2009; Stainier, Shah, and Barreca, 2026). Growing season precipitation averages 156 millimeters (mm), with high variability (92 mm) reflecting India's monsoon climate. This wide variation across districts and birth cohorts provides the necessary statistical power to isolate the "Heat Trap" from secular development trends.

Figure 2 displays density plots of in-utero temperature and precipitation exposure across districts and birth years. The temperature distribution exhibits a roughly normal shape centered near 26.5°C, with substantial mass in both tails. The precipitation distribution is more skewed, reflecting the high variability of monsoon rainfall. Importantly, there is substantial variation in both temperature and precipitation even within districts across different birth cohorts, providing the identifying variation for our analysis. The within-district standard deviation of temperature is approximately 2.5°C, indicating that year-to-year fluctuations provide meaningful variation in prenatal exposure even after accounting for permanent district characteristics.

Appendix Figure B1 presents binned scatter plots highlighting the negative relationship between in-utero temperature exposure and upward mobility in education and occupation separately. These raw associations reveal a clear pattern: higher average decadal temperatures in the growing

seasons during the year before birth are associated with lower mobility rates. The relationship appears roughly linear for temperatures above 24°C, with steeper declines at the highest temperatures. These unconditional correlations provide initial evidence that prenatal temperature exposure affects intergenerational mobility, though they do not account for potential confounding factors that our regression analysis will address.

Finally, Panels B and C document the baseline vulnerabilities that potentially mediate this trap. High rates of childhood anemia (32%) and maternal metabolic syndrome markers, alongside a significant incidence of household-reported losses and medical-expenditure-driven debt (8% of households)[4], suggest a fragile socioeconomic environment where chronic climatic stress during birth can have deleterious effects on long-run developmental trajectories.

4 Empirical Strategy

Our empirical strategy exploits exogenous variation in growing season temperatures across districts and birth years to identify the causal effect of prenatal temperature exposure on intergenerational mobility. We describe our baseline specification, identification assumptions, and estimation approach.

4.1 Baseline Specification

Our baseline regression specification takes the form:

$$y_{ihbds} = \sum_{g\in\{0,1\}} \beta_g T_{dg} + \sum_{g\in\{0,1\}} \zeta_g P_{dg} + \mathbf{X}'_{ih}\gamma + \lambda_d + \eta_b + \delta_m + b\phi_s + \varepsilon_{ihbds} \tag{1}$$

The dependent variable y_{ihbds} is a binary indicator of upward mobility (educational and occupational) for individual i in household h born in year b (month m) in district d and state s. T_{dg} is the average decadal temperature in degrees Celsius over the growing-season months (June through December, $g = 1$) and non-growing season months (March to May, $g = 0$) measured when an individual is in-utero. Analogously, P_{dg} is the average precipitation measured in millimeters for the decade ending when individual is in-utero. Following Stainier, Shah, and Barreca (2026) and Garg, Jagnani, and Taraz (2020), we focus on the impact of in-utero exposure to average decadal temperature in the growing season, controlling for the weather in non-growing season. Isolating the specific effect of in-utero exposure is critical for distinguishing between prenatal biological effects and persistent economic effects that might affect households over multiple years (Bhalotra and Clots-Figueras, 2014).

We estimate Equation 1 using ordinary least squares.[5] The use of a linear probability model for

[4] Appendix Figure B2 presents binned scatter plots emphasizing the positive unconditional correlations between household reported losses and medical loan and exposure to average growing season temperature, measured for the decade preceding the survey (Liu, Shamdasani, and Taraz, 2023; Stainier, Shah, and Barreca, 2026).

[5] All our estimates are obtained from unweighted regression specifications. Our results remain intact in weighted

binary outcomes facilitates interpretation of magnitudes and allows us to include high-dimensional fixed effects computationally efficiently.[6]

The specification includes a comprehensive set of fixed effects and controls. District fixed effects λ_d absorb time-invariant differences in mobility rates across locations, including persistent differences in educational infrastructure, labor market opportunities, and cultural attitudes toward mobility. Birth year fixed effects η_b control for national trends in educational expansion and occupational structure that affect all cohorts uniformly. Birth month fixed effects δ_m account for potential seasonality in temperature exposure and developmental timing, as children born in different months experience different trimesters of pregnancy during the growing season. State-specific linear time trends $b\phi_s$ flexibly control for differential trends in mobility across states, capturing diverging development trajectories that might be correlated with climate patterns.[7]

The vector $\mathbf{X}_{ih}$ represents individual and household demographic characteristics: gender, age, age squared, and marital status of individual, and fixed effects for father's educational levels and occupation category, and caste and religion of household. These variables control for compositional differences that may correlate with both temperature exposure and mobility outcomes. The inclusion of caste and religion fixed effects is particularly important in the Indian context, given the historical persistence of caste-based inequality and the well-documented differences in mobility rates across social groups (Hnatkovska, Lahiri, and Paul, 2012).

We cluster standard errors at the district level to account for potential serial correlation within each district over time. Additionally, we implement Conley (1999) standard errors to allow for spatial correlation up to 500 kilometers and arbitrary serial correlation in the error term (Liu, Shamdasani, and Taraz, 2023). This approach addresses concerns that temperature realizations may be correlated across nearby locations or across adjacent birth cohorts within the same district. We also verify robustness to two-way clustering by district and birth year, which accounts for correlation across districts within birth cohorts. Results are quantitatively and qualitatively similar under these different clustering approaches.

4.2 Identification

Our identification strategy relies on the assumption that, conditional on the vector of fixed effects and controls described above, variation in temperature across districts and birth cohorts is as good as randomly assigned. This assumption is plausible for several reasons.

First, year-to-year variation in temperature within districts is largely driven by exogenous atmospheric processes that remain independent of local economic conditions. While annual devi-

regressions using the survey weights provided in the survey to obtain estimates representative of the Indian population. We report these results in Appendix Tables B6.

[6] Our estimates are qualitatively identical to results from logistic regression specifications, which we discuss in Section 7.

[7] We construct linear time trends using the birth years of individuals. We examine alternate specifications with region-specific linear trends in birth year in lieu of state trends, using the six regional zones of the country. Our results are robust to accounting for state- or region-specific quadratic trends in birth year, which we discuss in Section 7 later.

ations from decadal averages represent stochastic weather realizations that primarily exert direct physiological or economic effects, the ten-year average prior to birth captures the prevailing climate distribution. Following Hsiang (2016), we utilize this decadal average to account for belief effects, the long-term structural adaptations and household expectations formed in response to the persistent climatic environment, which may independently influence residential and mobility decisions.

The inclusion of district fixed effects and state-specific time trends ensures that our estimates are not driven by permanent differences across locations or by smooth trends in climate and economic development. Our use of decadal averages further ensures that we capture persistent climate patterns rather than transitory weather fluctuations (Liu, Shamdasani, and Taraz, 2023; Burke and Emerick, 2016).

Second, the timing of births relative to temperature shocks is unlikely to be systematically related to unobserved determinants of mobility. Parents do not observe temperature realizations at the time of conception, which occurs roughly nine months before birth. Any selection on fertility timing would need to operate through expectations about future temperature conditional on historical patterns, which seems implausible given the high degree of year-to-year temperature variation. We verify empirically that temperature does not predict fertility or the composition of births, suggesting that selection on fertility is not a significant concern. Appendix Table B2 provides evidence for these null results using information on fertility (number of births in the last one year as on the date of survey) and the composition of births (whether the child born is a boy or girl, based on the birth order) from the NFHS 2015-16 survey.

Third, we provide evidence that our temperature effects are not confounded by variation in precipitation, which is the primary climate variable affecting agricultural production in monsoon-dependent regions in India (Jayachandran, 2006). To do so, we substitute the average decadal precipitation levels with two alternate measures of precipitation across different model specifications. Following Stainier, Shah, and Barreca (2026), we first construct a "rainfall shock", which takes a value equal to 1 if rainfall in a given district-season-year exceeded the 80^{th} percentile of our sample distribution (1949-1996) of rainfall for that district-season, and value equal to -1 if rainfall was below the 20^{th} percentile of the sample distribution, and zero otherwise (Shah and Steinberg, 2017). The second measure involves separate wet (positive rainfall) and dry (negative rainfall) shocks, which each take a value equal to one if the rainfall was above the 80^{th} percentile or below the 20^{th} percentile, respectively. These measures capture extreme precipitation events that may independently affect fetal development and household economic conditions.

A potential threat to identification would arise if temperature shocks trigger migration of families to locations with different baseline mobility rates. However, internal migration in India is relatively limited, particularly for the cohorts in our sample, and most migration occurs for employment reasons rather than in response to weather shocks (Munshi and Rosenzweig, 2006, 2016). Moreover, if migration occurs, it likely represents an adaptive response that would attenuate our estimates, implying that our results provide a lower bound on the true effect of temperature

exposure for non-migrating populations.[8]

Another concern is selective mortality: if temperature shocks increase infant mortality differentially by family background, then survivors in our sample may be positively selected on unobserved health endowments. This selection would bias our estimates toward zero if it is stronger among disadvantaged families, as surviving children would have higher latent ability than the population average. Empirically, we find no evidence of differential mortality by parental occupation in response to temperature shocks using available mortality data from NFHS 2015-16 , alleviating this concern. Appendix Table B1 rules out any statistically significant impacts on infant mortality and neo-natal mortality across wealthier and poorer households. This finding is consistent with temperature shocks affecting development and human capital accumulation without substantially increasing mortality risk based on household endowments in our sample period.

Our results stand intact in an extensive battery of rigorous robustness and sensitivity tests. We ensure that these checks address potential concerns regarding unobserved spatial and serial dependencies, alternative functional forms for both the explanatory and the outcome variables, and the potential for confounding regional developmental trajectories. By systematically varying the underlying model specifications, including adjustments for sampling representativeness, the inclusion of non-linear trends, and the decoupling of heat from rainfall variation, we ensure that our findings are structurally sound. The stability of our point estimates and their consistent statistical significance across these diverse specifications reinforce the validity of the "Heat Trap" and confirm that the identified effects represent a persistent biological and economic phenomenon rather than a byproduct of specific modeling choices. We discuss these later in Section 7.

5 Results

5.1 The Intergenerational Heat Trap: Mobility in Education and Occupation

Our core findings, presented in Table 2, establish a significant and negative relationship between in-utero heat exposure and long-run educational mobility. We find that extreme temperatures during the growing season (GS) act as a structural barrier, "trapping" individuals in lower educational strata than their parents.

Panel A reports the impact on our primary binary indicator for upward mobility in education: Intergenerational Educational Mobility (IEM_i) (Alesina et al., 2021). Across all specifications, we find a negative and statistically significant relationship between GS temperature and IEM_i. In our most preferred specification (Column 3), which accounts for district fixed effects, individual demographics, and state-specific linear trends in birth year, we document that a 1 °C increase in GS temperature reduces the probability of upward educational mobility by 10.5 percentage

[8]Following Dasgupta, Majid, and Orman (2023), we address migration-related concerns in all our health-related analyses using the NFHS 2015-16 survey, by accounting for the number of years an individual has stayed in the current place of residence. Our primary outcomes on intergenerational mobility constructed from the IHDS 2011-12 survey also stand intact, after accounting for individuals who migrated into the their current district of residence five years ago or less.

points, ceteris paribus.[9] Given the outcome mean of 0.566, this represents a substantial 18.5% reduction in the likelihood of a child surpassing their father's educational attainment.

Panel B reinforces this finding using the Child's Education Rank: a $1°C$ increase in in-utero heat exposure pushes down a child by 3.3 percentiles in the national education distribution (Column 3). This shift is not merely a localized drop in schooling years but a fundamental decline in an individual's relative standing within their cohort, which can have profound implications for labor market competitiveness.

To examine persistence among the most vulnerable, Panel C shows that a $1°C$ increase in GS temperature reduces the propensity of Bottom Quartile to Upper-Half Mobility ($Q1UH$) by 2.1 percentage points (Column 3). This is a staggering effect considering the mean for this specific mobility is only 0.058, resulting in almost 36.20% decline in the probability of of a child from the most disadvantaged background reaching the upper half of the educational distribution.

The impacts extend beyond educational attainment, fundamentally altering the occupational trajectory of individuals. While education represents a potential for progress, occupational mobility represents the realization of that progress in the labor market. Table 3 demonstrates that in-utero heat exposure significantly hinders the transition from traditional to modern sectors.

Panel A shows that a $1°C$ increase in GS temperature reduces Intergenerational Occupational Mobility IOM_i by roughly 4.6 percentage points (Column 3). Relative to the mean of 0.427, this implies a roughly 11% reduction in the likelihood that an individual attains a higher-status occupation than their father, suggesting that the damage from heat exposure creates a "performance gap" that persists even after schooling is completed.

Panel B focuses on the most important transition for structural transformation: the movement out of the Agricultural to Non-Agricultural sectors. Individuals exposed to an additional $1°C$ increase in in-utero GS temperature are about 4 percentage points less likely to escape the agricultural sector. Given that agricultural labor in India is often synonymous with low productivity and high vulnerability, this finding indicates that heat shocks are a significant driver of the rural poverty trap.

Panel C utilizes a more critical measure: Human Capital Intensity based Occupational Mobility, which ranks occupations by the skill level required (Brahma, 2025; Ahsan and Chatterjee, 2017). We find a consistent negative impact of 4 percentage points for an additional $1°C$ increase in GS temperature. This confirms that even when individuals move into non-farm work, heat exposure pushes them into low-skill, low-intensity roles (blue collar) rather than high-skill professional roles (white collar).

We note two synthetic patterns that underscore our argument for the relationship between in-utero heat exposure and intergenerational mobility. First, while GS temperature is a strong negative predictor, GS precipitation remains statistically insignificant for all the mobility metrics

[9]Based on the coefficient in Column 3 of Table 2, a one-standard-deviation increase in in-utero exposure to average growing season temperature reduces the probability of upward mobility in education by 25.2 percentage points ($p < 0.01$), where the effect of growing season precipitation is statistically insignificant.

irrespective of the econometric specification. This suggests that the "Heat Trap" is not merely a proxy for rainfall-driven agricultural shocks but is a distinct and more potent thermal phenomenon, in contrast to much of the early climate literature focusing on rainfall shocks. Second, the notable stability in the magnitude of the GS temperature effect as we move from the vanilla OLS specification towards the fixed effects models emphasizes the persistence of the effect, even after filtering out state- or region-specific development trends, thereby confirming that we are capturing a genuine climatic shock rather than a correlation with broader regional stagnation.

While our mobility metrics capture the intergenerational shift, Table 4 documents the absolute erosion of human capital and the structural regression in labor choices caused by in-utero heat exposure. These results provide a life-cycle view of how the heat trap manifests from childhood through adulthood.

First, in Panel A, we find that in-utero heat exposure significantly lowers the probability of completing every major educational milestone. The impact is not confined to higher education but begins as early as the primary level, suggesting that the heat trap triggers an early exit from the schooling system, likely due to impaired cognitive development or early-life economic necessity (Garg, Jagnani, and Taraz, 2020). Statistically, we observe a 6 and 9 percentage points reduction in the likelihood of completing primary and elementary schooling respectively, with the negative pressure continuing through high school (about -4 pp) and university (-4.8 pp).

The results on occupational choices in Panel B reveal a distressing push factor: heat exposure not just reduces the quality of jobs; it forces individuals back into the most volatile and low-productivity sectors of the economy. An additional $1°C$ of GS temperature increases the probability of an individual remaining in agricultural occupations by 4.0 percentage points. This suggests that heat shocks stall the structural transformation of the labor force, keeping families tethered to the land. More importantly, we find a 4.3 percentage point increase in the likelihood of engaging in Casual Work ($p < 0.05$). Since casual labor in India lacks social security, stability, and growth prospects, this result identifies in-utero heat as a primary driver of lifelong economic precariousness.

These findings are indicative of a double disadvantage created by in-utero heat exposure: it first pulls down individuals along the educational ladder, and then systematically channels them into the least productive and most vulnerable sectors of the labor market.

5.2 Mechanisms

We now deconstruct the underlying economic and biological channels through which an in-utero thermal shock translates into a life-cycle of reduced mobility. Following the tradition of the "Quality-Quantity" trade-off (Becker and Tomes, 1979) and the "Dynamic Complementarity" of human capital (Cunha and Heckman, 2007), we hypothesize that the Heat Trap operates through two primary conduits. First, we examine the Household Budget Constraint channel, where heat acts as a systemic shock to productivity and health, triggering distress-based economic

decisions. Second, we investigate the Biological Endowment channel, where in-utero exposure directly impairs the health and cognitive potential of the fetus.

5.2.1 Household Effects

We examine how heat exposure impacts household-level stability. While our primary identification relies on individual in-utero windows, we provide the contemporary economic backdrop of vulnerability among households using information from the Household module of IHDS 2011-12 by studying the impact of average temperature and precipitation, for each district-season, measured for the decade ending in 2010. Table 5 shows contemporaneous impacts of average decadal GS temperature on household-reported losses and medical-driven-debt.

Column 1 reports our Household Loss Index, a composite z-score of household-reported losses. We observe a statistically significant increase in this index ($\hat{\beta} = 0.073$, $p < 0.01$), confirming that heat is not a localized agricultural issue but an aggregate shock that can destabilize the entire domestic unit.

We document a striking evidence of a trap mechanism in Columns 2 and 6: an additional 1 °C of average decadal GS temperature increases the probability of a major loss or accident by 1.8 pp, and critically increases the probability of taking a medical loan by 1 pp. In the absence of universal health insurance, medical shocks become a leading cause of falling into poverty traps (Krishna, 2011). Taking a medical loan to combat heat-induced illness creates a binding liquidity constraint, forcing the households to divert resources away from their children's education and into debt servicing. This aligns with Jayachandran (2006), who argues that under-developed credit markets transform temporary weather shocks into permanent welfare losses.

Column 4 shows a 2 pp increase in propensity of job loss per 1 °C increase in GS temperature. This supports the heat-productivity framework, suggesting that extreme heat reduces the physical capacity for labor, leading to income volatility (Heal and Park, 2016; Somanathan et al., 2021). We also note a 0.7 pp increase in the chances of other economic losses (Column 5).

5.2.2 Health Effects

While the household economic losses create a restrictive investment environment, the "heat trap" is anchored by a deeper, biological phenomenon: the fetal-origins of long-run mobility. Following the Barker Hypothesis (1990) and the seminal fetal origins literature (Almond, 2006; Almond and Currie, 2011), we argue that in-utero heat exposure acts as a primary biological shock that strongly impairs the initial endowment of human capital.

Maternal Health: We first shed light on Table 6, which provides evidence that heat exposure during pregnancy triggers a systemic physiological decline in mothers. Using the Metabolic Syndrome Index, a comprehensive index of standardized z-scores of high blood pressure, diabetes, heart diseases and obesity, constructed following Sekhri and Shastry (2024) and Hoynes,

Schanzenbach, and Almond (2016), we find that a 1 °C increase in GS temperature significantly elevates maternal health risks ($\hat{\beta} = 0.027$, $p < 0.01$) as shown in Column 1.

Columns 2 through 5 present a breakdown of this index to reveal a broad spectrum of thermal stress. GS temperature exposure significantly increases the probability of high blood pressure (1.0 pp), diabetes (0.3 pp), and heart disease (0.3 pp). These are not merely adult-onset conditions but indicators of the maternal environment's quality. Column 5 shows a 0.7 pp increase in maternal obesity, measured as per the World Health Organization (2025). This aligns with research on metabolic programming, where early-life environmental stress alters the body's ability to regulate energy, potentially leading to long-term inflammation and metabolic dysfunction (Sekhri and Shastry, 2024). We also observe a significant 0.2 pp increase in the likelihood of suffering from asthma (Column 6). These findings help us to identify the transmission mechanism: the mother's health acts as a biological conduit, passing through the environmental stress of the heat exposure directly to the developing fetus.[10]

Child Health: We now establish our fetal origins hypothesis with respect to the heat trap. We trace the life-cycle of the developmental deficit to document a cascading failure of human capital formation, starting from birth outcomes and progressing through neonatal fragility to childhood developmental indicators. We report these results in Table 7 through three evolutionary stages.

The biological effect begins with neonatal fragility: a $1°C$ increase in growing season temperature during gestation reduces the likelihood of a child being born at a normal or large size by 4.8 pp and the probability of low birth weight by 5.4 pp.[11] These are primary indicators of the initial endowments (Almond, Currie, and Duque, 2018). Thermal stress triggers maternal inflammatory responses and placental insufficiency, depriving the fetus of critical nutrients. Following the Barker Hypothesis 1990, these neonatal deficits represent a permanent setting of the individual's physiological and metabolic capacity.

Moving towards post-birth maternal-child interactions and health resilience, find a significant increase in the delay of breastfeeding initiation (13.3 pp) and immune fragility in terms of greater likelihood of suffering from diarrhea (22.2 pp), potentially owing to impaired immune function and cognitive trajectory (Dasgupta and Sharma, 2024), besides increased susceptibility to environmental pathogens even months after birth.

[10] In line with Stainier, Shah, and Barreca (2026) and Liu, Shamdasani, and Taraz (2023), we complement our analysis on major morbidity with contemporary evidence from the IHDS 2011-12 survey, where we examine the effects of average decadal temperature measured in the end of 2010. This exercise serves to validate our health mechanisms by examining whether individuals residing in hotter districts exhibit deleterious health outcomes. Adult health reflects the cumulative effects of early-life conditions, including *prenatal* and early childhood environments, and thus provides informative evidence on biological scarring. Consistent with this mechanism, we find statistically significant associations between long-run district-level temperature and multiple health outcomes in the IHDS. We show these results in Appendix Table B15, thereby reinforcing our argument that prenatal heat exposure affects intergenerational mobility through persistent impacts on human health.

[11] Following World Health Organization (2022), we define low birth weight as weight of child at birth less than 2.5 kilograms. Low birth weight has been attributed to intrauterine growth restriction, prematurity or both, and is strongly associated with fetal and neonatal mortality and morbidity, impaired postnatal growth trajectories and adverse neurodevelopmental outcomes, including deficits in cognitive function (World Health Organization, 2014).

The third stage of the biological cascade marks the physical manifestation of long-term developmental stalling. We also document increased probability of stunting (24.2 pp), wasting (10.3 pp), and being underweight (21.7 pp), associated with in-utero exposure to growing seasons temperature. Finally, we also note a significant increase in the likelihood of the child being severely anemic, defined according to WHO guidelines (USAID, 2017). These results provide a definitive empirical link to the model of dynamic complementarity, i.e., skills beget skills and health begets health (Cunha and Heckman, 2007). The in-utero heat shock creates the initial deficit, which reduces the marginal productivity of postnatal investments, resulting finally in the structural developmental stall.

By moving beyond the conventional income or economic shock framework, the above results on health effects help in establishing that in-utero heat exposure functions as a systemic biological tax that gets levied before birth. Extreme growing season temperature breaches the shield of maternal health, thereby affecting the child during birth. Furthermore, by creating early childhood nutritional gaps, in-utero heat exposure induces a state of immunological fragility, making the children biologically less capable of sustaining the cognitive demands in school. Our findings demonstrate an intergenerational sorting mechanism: in-utero weather conditions dictate the ceiling of adult achievements.

5.2.3 Bridging Health and Mobility

While the above results on health effects established the physiological impacts of in-utero heat exposure, we now bridge these early life deficits and the long-run intergenerational outcomes. To that end, we employ a mediation framework to test whether the "Heat Trap" documented in Section 5 is, at its core, a health trap. Using information on major health morbidities from the individual module of the IHDS survey, we construct a binary indicator for *Major Health Morbidity*, equal to one if an individual suffers from any of fourteen major morbidities, including high blood pressure, heart disease, diabetes, cancer, asthma, and others, and zero otherwise. We isolate the amount of variation in this mediator explained by in-utero exposure to weather conditions using Equation 1, and then use this predicted health deficit (post standardization) to analyze upward mobility in education.[12]

Table 8 presents the results of this mediation framework. Columns 1 and 3 show that a one-standard-deviation increase in the predicted major health morbidity reduces intergenerational educational mobility (IEM) by 18.6 pp and bottom quartile to upper-half mobility ($Q1UH$) by

[12]While the OLS based mediation analysis provides strong suggestive evidence for our health channel, we subject it to a more formal and rigorous test using a Two-Stage Least Squares (2SLS) Instrumental Variable approach. Here, we explicitly instrument the Major Health Morbidity score (ranging from 0 to 2) with in-utero exposure to growing season temperature, by relying on the plausible exogenity of in-utero exposure to weather (Maccini and Yang, 2009; Adhvaryu et al., 2024). Appendix Table B14 presents the results for this IV estimation framework, where the Kleibergen-Paap Wald F-Statistic (>10) shows the strength of our instrument, confirming that in-utero thermal stress is a sufficiently strong predictor of adult health morbidity. By controlling for GS precipitation and non-growing season weather, we isolate the biological thermal channel through which in-utero heat affects educational mobility.

6.9 pp, where the effect of GS temperature loses its significance. Furthermore, Column 2 reports about 10 percentile decline in the education rank of the child. These results show the shadow price of in-utero thermal stress, and rationalize our primary documented impacts on mobility metrics that growing season temperature strikes at the crucial foundation of human capital: health.

5.3 Intensity and Persistence of the Heat Trap

5.3.1 The Temporal Window of Vulnerability: Why In-Utero and Early Childhood Matter

A primary concern in the climate-development literature is whether identified effects are merely contemporaneous economic shocks or deep-seated "developmental scars". While recent works have focused on annual temperature fluctuations and current test scores (Garg, Jagnani, and Taraz, 2020; Shah and Steinberg, 2017), labor re-allocation (Liu, Shamdasani, and Taraz, 2023) or rural household-diets and nutrition (Stainier, Shah, and Barreca, 2026), our approach shifts the focus to the intergenerational origin of these disparities.

Panel A of Figure 3 presents the impact of average GS temperature from our baseline specification with region-specific linear trends in birth year and other controls by varying the timing of the exposure. The results reveal a striking "inverted-U" pattern of vulnerability.

We first note the critical window (exposure age: -1 to 3 years), wherein the negative impact on Intergenerational Educational Mobility (IEM_i) begins to materialize in the pre-conception period ($t = -3$), intensifies significantly in-utero ($t = -1$, $\hat{\beta} = -0.110$), and reaches its peak magnitude during early childhood ($t \in (1, 3)$). The strong statistical significance of in-utero exposure supports the *Fetal Origins Hypothesis* (Almond, 2006; Maccini and Yang, 2009). The persistence and peaking of the effect through exposure age of 3 years aligns with the critical window of brain development and nutritional plasticity (Almond and Currie, 2011). Shocks during this period are known to have "multiplier effects" on human capital, as early-life deficits make subsequent schooling investments less productive (Cunha and Heckman, 2007).

Crucially, the "Heat Trap" is not a constant weight throughout the life-cycle. As individuals move past age 10 years, the coefficients steadily attenuate toward zero and lose statistical significance. This suggests that the biological window of plasticity closes as children reach adolescence. This is a vital distinction: if heat were just a proxy for general regional poverty, we would expect a constant negative effect regardless of the timing. Instead, our results prove that the timing of exposure is the primary determinant of intergenerational failure.[13]

By documenting this specific life-cycle trajectory, we move beyond the contemporaneous weather shock framework of the existing literature. Besides the impact on current educational and

[13]While the emergence of significance at $t = -4$ might appear as a pre-trend in the conventional econometric setting, in a life-cycle context, this likely reflects the maternal health environment and household resource accumulation prior to conception. Crucially, the coefficients for distant pre-birth years ($t < -10$) are precisely estiamted zeros, effectively ruling out the concern that our results are driven by long-standing regional omitted variables or "spurious" developmental trends.

occupational outcomes, we demonstrate that chronic climatic stress during the in-utero and early childhood years sets a ceiling on mobility that persists for decades. In this process, we link the *Barker Hypothesis* directly to the long-run intergenerational rank of individuals in a developing economy, providing a structural explanation for why regional heat traps are so difficult to escape.

5.3.2 The Cumulative Burden: Validating the Decadal Exposure Window

A pivotal question in the fetal origins literature is whether long-run outcomes are driven by a single, acute environmental shock or by the chronic accumulation of stressors during the critical developmental window. To address this, we estimate a dose-response relationship between in-utero heat exposure and intergenerational educational mobility, by systematically varying the exposure window, measured in-utero. Panel B of Figure 3 highlights a critical scale effect imposed on educational mobility with respect to the intensity of in-utero exposure to growing season temperature.

While a single year of in-utero heat exposure generates a statistically significant negative impact ($\beta = -0.017$, $p < 0.05$), this effect increases five-fold in our baseline decadal exposure window, suggesting that intergenerational mobility is not merely sensitive to a one-off weather event, but is fundamentally constrained by the thermal regime of the district. This aligns with Currie and Vogl (2013), who argue on the persistence of environmental hardship in determining the depth of the long-term human capital deficit.[14]

The pattern in the plot rationalizes our choice of a decadal exposure (Liu, Shamdasani, and Taraz, 2023): at lower lags (1-3 years), the estimated impacts are smaller in magnitude and growing, plausibly reflecting the noise of idiosyncratic annual fluctutations. However, as the horizon expands, the coefficients show a stabilizing effect. This confirms that, while early-life shocks are critical, the total environment of the mother and household, shaped over a longer horizon, sets the baseline for the child's biological and economic potential. A single hot year might be weathered by selling small assets or borrowing. However, a decade of heat exposure can exhaust household savings, degrade local health infrastructure, and permanently lower the return on schooling investment.

[14]We acknowledge the theoretical argument by Hsiang (2016) that, the marginal effect of weather shocks should identify the total effect of climate because marginal adaptations yield zero net benefit. However, this equivalence is less likely to hold in our context for three structural reasons. First, the Envelope Theorem assumes agents are at a smooth, interior optimum; yet in the presence of the binding credit constraints and corner solutions prevalent in rural India (Burgess and Pande, 2005), households cannot marginally adapt away the biological distress caused by heat exposure. Second, as compared to contemporaneous outcomes like agricultural outputs, educational outcomes, or occupational choices; intergenerational mobility maps a path-dependent human capital accumulation process, making it sensitive to the cumulative exposure to environmental stressors rather than to transitory annual shocks. Finally, biological scarring during the in-utero window represents a non-marginal, irreversible physiological change that bypasses the economic logic of marginal adjustment. As Panel B of Figure 3 shows, the escalating magnitude of coefficients alongside the expansion of exposure window empirically rationalizes and validates our argument and identification.

6 Heterogeneity

While our baseline results establish a robust negative link between in-utero heat exposure and intergenerational educational mobility, thereby strengthening our fetal origins argument, we test whether important demographic and institutional dimensions can attenuate the long-run mobility penalty in an interaction framework, allowing for variation in the net effects of temperature and precipitation (Liu, Shamdasani, and Taraz, 2023).[15]

6.1 Heterogeneity across Household Demographics

We first examine whether the heat trap has differential impacts on the children of uneducated and/or agricultural fathers: a poverty trap, or having fathers with some education or working in skilled occupations helps by mitigating a systemic biological tax on entire distribution of potential. In particular, we examine whether parental endowments acts as a buffer against environmental shocks. Table 9 clearly shows that the negative impacts documented on educational mobility (IEM_i) in Table 2 are strongly driven by individuals whose fathers have some education (Column 1) and are working in blue collar and white collar occupations (Column 2). Although counter-intuitive, this suggests that the heat trap doesn't just prevent the poor from rising, but also pulls the middle class downward, eroding the gains of prior generations. The in-utero heat shock induces a physiological effect upon these individuals that prevents them following their fathers' educational trajectory.

Next, we highlight a critical intersection between temperature shocks and social divisions: differential impacts across Muslim versus non-Muslim households.[16] Despite this group's specific

[15] We augment our baseline specification shown in Equation 1 by interacting all the weather variables with binary indicators as follows

$$y_{ihbds} = \sum_{g\in\{0,1\}} \beta_g T_{dg} + \sum_{g\in\{0,1\}} \zeta_g P_{dg} + \sum_{g\in\{0,1\}} \beta_{\Gamma g}(T_{dg} \times \Gamma) + \sum_{g\in\{0,1\}} \zeta_{\Gamma g}(P_{dg} \times \Gamma) + \mathbf{X}'_{ih}\gamma + \lambda_d + \eta_b + \delta_m + b\phi_s + \varepsilon_{ihbds}$$

where Γ is a binary indicator capturing a particular household demographic (h) or district-level institutional (d) heterogeneous feature. This setup helps in identifying the effects of growing season temperature for the two sub-groups separately (Liu, Shamdasani, and Taraz, 2023). We explore differential impacts among educated vs uneducated fathers, agricultural vs non-agricultural fathers, muslim vs non-muslim households, male vs female individuals, urban vs rural households; and above median verus below median of the distribution for bank density (number of banks), health infrastructure (number of hospitals, dispensaries, clinics, health centers, etc. along with the number of beds in the respective places), government expenditure (spending on public administration, safety, health, works, etc.); electricity infrastructure (total domestic, industrial, commercial, and road lighting electrical connections), and total irrigated land in rural areas in the districts. We capture information on these district-level infrastructure from the 2001 Population Census, conducted about a decade prior to the IHDS survey in 2011-12.

[16] We explore this heterogeneity result, motivated by recent evidence from Asher, Novosad, and Rafkin (2024), who document a sharp divergence in the mobility trajectories of India's marginalized groups. While Scheduled Castes (SCs) and Scheduled Tribes (STs) have seen modest gains in upward mobility over the last three decades, thereby narrowing the gap with the upper castes, upward mobility among Muslims has declined substantially. By ruling out differential fertility, geography, and differential occupational patterns, Asher, Novosad, and Rafkin (2024) rely on affirmative action to rationalize the SC/Muslim divergence. This could function as partial insurance mechanisms against intergenerational persistence. Considering possible differences in baseline educational attainment and asset ownership across social groups, climate-induced shocks may interact with pre-existing human capital distributions in heterogeneous ways. A comprehensive investigation of these mechanisms, however, is beyond the

demographic weight in our working sample, we document a strongly significant negative impact on educational mobility for Muslim households in Column 3 ($\hat{\beta} = -0.038$, $p < 0.01$) vis-à-vis their counterpart. This is suggestive of a compounding marginalization effect: for a group already characterized by declining mobility and limited opportunities for social ascent, the physiological stress of in-utero heat exposure acts as a binding constraint.

The most striking findings for our fetal origins narrative are the null heterogeneous results in Columns 4 and 5, indicating gender neutrality and urban neutrality respectively. The muted significance of these interactions suggests that the heat shock operates through maternal-fetal physiology, where neither parental preferences over their child can intervene, nor the urban infrastructure of their residence can provide any significant shield against the physiological effects of rising temperatures during gestation. These results provide strong empirical weight to our argument that we are observing a biological rather than the conventionally posited economic phenomenon.

6.2 Heterogeneity across Institutional Contexts

Literature highlights the role of institutional buffers and support in mitigating the deleterious effects of weather shocks. If the heat trap primarily operates through an income channel, for e.g., crop failure resulting in nutritional deficits (Stainier, Shah, and Barreca, 2026), then district-level institutions, capturing the adaptive capacity and resilience of districts should, theoretically, attenuate the shock. However, if the impact is driven by direct physiological or neuro-developmental fetal effects, these postnatal and meso-level buffers may prove ineffective. We test our insignificant institutional buffer hypothesis by employing the same weather-interaction framework to test for differential impacts in districts classified on the basis of median of distribution of different infrastructural capacities, which we source from the 2001 Population Census.

We present these results in Table 10. Column 1 rules out the differential effects of banking infrastructure, by showing insignificant effect of above median number of banks, a conventional proxy for credit availability and the ability of households to smooth consumption against transitory shocks (Burgess and Pande, 2005), in moderating the negative effects of growing season temperature on educational mobility.[17] Column 2 shows a critical result: null interaction for

scope of the present paper.

[17] Our documented result of banking infrastructure neutrality might stand in apparent tension with influential evidence on the role of credit markets in climate adaptation. Most notably, Liu, Shamdasani, and Taraz (2023) present strong effects of rising average temperatures on the share of agricultural laborers and the share of nonagricultural workers, completely driven by districts with below-median bank credit per capita at baseline. In another literature, Cramer (2025) utilizes a large-scale bank branch expansion to show that improved financial access bolsters household resilience and healthcare utilization. We reconcile our null interaction effects with these findings by highlighting two fundamental distinctions in our framework: the biological focus of the in-utero window and the longevity of developmental trajectories. Liu, Shamdasani, and Taraz (2023) and Cramer (2025) establish behavioral adaptations to economic volatility: banking infrastructure provide households with the liquidity and mobility required to smooth consumption or reallocate labor in the face of contemporaneous shocks. However, our focus on in-utero exposure is grounded on a physiological shock. Following the fetal origins literature (Almond, 2006; Almond and Currie, 2011), extreme heat during gestation induces maternal stress, placental insufficiency, and inflammatory responses that program the the fetus's future health and cognitive potential, implying that the

temperature and above median number of hospitals, dispensaries, clinics, health centers, beds, etc., strengthening our fetal origins argument. This highlights the physiological effect of heat, occurring during the in-utero window, in a way that standard local medical facilities cannot repair the developmental damage once it has occurred.

We further find that neither state capacity nor technological safeguards provide any shield against in-utero heat shocks. These are shown in Columns 3 though 5, ruling out differential effects across above median vs below median levels of government spending on public administration, safety, health, works, etc. (Column 3), total domestic, industrial, commercial, and road lighting electrical connections (Column 4), and total irrigated land in rural areas (Column 5) in districts. These results suggest that broad-based provision of public goods are not sufficiently calibrated to protect fetal health from thermal stress: neither they can provide considerable financial buffer or domestic cooling, nor they can decouple local agricultural yields from weather.

The consistent null results across all the infrastructural based interaction models constitutes a major empirical finding by providing the smoking gun for the fetal origins hypothesis as the primary driver of the heat trap. The biological deficit due to the in-utero thermal stress is not a poverty trap, that can be solved by a bank or a hospital/clinic; neither administrative support can help mitigate its effects. It is a structural biological tax that persists regardless of a region's developmental stage. This underscores the necessity of focusing on preventative maternal cooling and prenatal care rather than relying on general institutional growth to solve climate-induced mobility stalls.

The persistence of the effects across different dimensions underscore the fact that in-utero temperature shocks pose a systemic risk that can transcend generations, irrespective of household endowments, or occupational background, or baseline developmental conditions.

7 Robustness and Sensitivity

To ensure that our baseline findings are not driven by our econometric specifications or functional form assumptions, we subject our baseline estimates to a comprehensive suite of robustness and sensitivity tests.

First, we show robustness to alternative forms of clustering. We begin with addressing spatial clustering of weather patterns and mobility outcomes by implementing (Conley, 1999) standard errors methodology. Following Liu, Shamdasani, and Taraz (2023), we allow for spatial correlation between districts up to 500 kilometers and account for arbitrary serial correlation in the error term. Appendix Table presents these results, confirming that the negative impact of in-utero

biological scar is institutionally inelastic. A second critical distinction lies in the temporal horizon of the outcomes. While the existing literature have addressed contemporaneous outcomes observed in the immediate aftermath of weather shocks, our focus on intergenerational educational mobility captures the cumulative realization of human capital over a lifetime. Even if a district gets a robust banking infrastructure (Cramer, 2025; Sedai et al., 2025; Gupta and Sedai, 2023), these postnatal resources are applied to an affected biological foundation, which make it difficult for new institutional capacities to neutralize the induced damages.

heat exposure is not driven by localized geographic clusters. We also test for general two-way clustering of the standard errors at district × birth year level and find that our baseline results hold, without any effects on the significance of those obtained from conventional clustering at the district level. These results are reported in Appendix Tables B3 and B4.

Second, we assess the robustness of our results for the binary mobility metrics, Intergenerational Educational and Occupational Mobility (IEM_i and IOM_i), to alternative model specifications. We re-estimate those regressions using a logistic specification, as opposed to the linear probability model (LPM) employed in the baseline analysis. Appendix Table B5 shows these estimates, which are qualitatively identical to the LPM, with consistent signs and significance levels across all specifications.

Third, we test the sensitivity of our results to alternative definitions of the temperature and precipitation measures (Liu, Shamdasani, and Taraz, 2023). We replace the original weather variables with *average weather across all the grid points* falling within a district's boundary. Appendix Table B7 shows that the results hold under this alternate construction of the weather variables. To ensure that our results are not driven by outliers or the inherent skewness of temperature and precipitation levels, we substitute the original weather variables with their logarithmic forms. From the results reported in Appendix Table B8, the persistence of the negative coefficient for growing season temperature, with a stronger magnitude, underscores the stability of the relationship across the distribution.

We also employ a flexible temperature bin specification to capture potential nonlinearities in the relationship between temperature and educational mobility without imposing a particular functional form. We define temperature bins covering ranges from below 20°C to above 34°C in intervals of 2 degrees (Stainier, Shah, and Barreca, 2026; Garg, Jagnani, and Taraz, 2020; Hsiang, 2016). Appendix Table B9 presents these results highlighting a monotonic escalation in the heat gradient: relative to the reference bin (< 21°C), every subsequent growing season temperature bin carries a progressively heavier penalty on educational mobility (Columns 1 and 2). The nonlinearity is more pronounced for Child's Education Rank (Columns 3 and 4). This bin specification serves two roles in our narrative: it suggests that the body's thermo-regulatory defenses are overwhelmed nonlinearly; and the baseline linear results are not being driven by a few extreme weather events, but rather by a consistent, escalating pattern of thermal stress.

Fourth, to confirm that our findings are not specific to the IHDS sample but are representative of the broader Indian population, we re-estimate the regressions using the sampling weights provided by the survey. Appendix Table B6 shows these results, which are both qualitatively and quantitatively similar to our baseline models, thereby suggesting that the identified mobility trap is a generalizable phenomenon across the national demographic.

Temperature and precipitation are often highly correlated (Hsiang, 2016). To isolate the heat effect from moisture-driven productivity shocks, we replacing the level forms of precipitation with the rainfall shock variables, separated by seasons. We do not find any significant changes in the magnitude or significance of our growing season temperature estimates, confirming that

heat exerts a distinct biological and economic pressure independent of rainfall variability. These results are shown in Appendix Tables B10 and B11 for the mobility outcomes for education and occupation respectively.

Finally, we relax our adoption of linear trends in birth year, which might be insufficient if the expansion of educational infrastructure or structural transformation in India followed a non-linear trajectory. We substitute the state- or region-specific trends linear trends in birth year in our baseline regressions for mobility metrics with respective quadratic trends in birth year, allowing the model to capture accelerating or decelerating changes in the regional economic environment. Appendix Tables B12 and B13 provides evidence for the robustness of our baseline results to these flexible trends. This strengthens our argument for the negative relationship between in-utero exposure to growing season temperature and intergenerational mobility rather than a mere convergence in regional educational patterns.

7.1 Limitations

In light of the potential for selection and behavioral responses to confound our primary estimates, a few methodological considerations warrant discussion. While our empirical framework accounts for birth location and controls for internal migration within the last two decades, the potential for endogeneity in compensatory parental investments remains a central challenge. Specifically, the observed persistence in intergenerational outcomes may reflect not only the direct biological damage to the fetal endowment but also subsequent household decisions to reallocate resources in response to early life shocks. Furthermore, the reliance on the IHDS necessitates an acknowledgment of the inherent limitations in respondent recall and the potential for measurement error across heterogeneous contexts. These factors suggest that our results should be interpreted as the net result of both biological vulnerabilities and the behavioral constraints characterizing the developmental environment.

8 Conclusion

This paper documents a mechanism through which the physical climate shapes the social order across generations. Exploiting within-district variation in decadal growing season temperatures across birth cohorts, conditional on district fixed effects and state-specific trends, we show that in utero heat exposure acts as a structural tax on intergenerational mobility. A one degree Celsius increase in prenatal growing season temperature reduces the probability that a child surpasses her father's educational attainment by 10.5 percentage points, pushes her 3.3 percentiles down the national education distribution, and makes her 36.2 percent less likely to escape the bottom quartile of attainment entirely. Occupational consequences are equally severe: the same thermal shock reduces intergenerational occupational mobility by 4.6 percentage points and raises the probability of casual wage employment by 4.3 percentage points. These estimates are stable across twelve robustness specifications and orthogonal to precipitation shocks throughout.

The mechanism operates through two reinforcing channels. The biological endowment channel runs through maternal health: heat during pregnancy elevates a composite Metabolic Syndrome Index, raises childhood anemia by 12.9 percentage points, and produces immunological deficits that reduce the cognitive returns to subsequent schooling investment. The resource depletion channel operates in parallel, raising the probability of medical indebtedness by 1 percentage point and household job loss by 2 percentage points, forces that divert resources away from children at the precise moment their biological vulnerability is highest. A mediation analysis confirms that the majority of temperature effect on educational mobility passes through adult health, consistent with the dynamic complementarity of endowments and investments (Cunha and Heckman, 2007). The life-cycle falsification seals the identification: the mobility penalty materializes in utero, peaks through age three, and attenuates to statistical zero by adolescence, ruling out the alternative that temperature proxies for a persistent regional poverty gradient.

Two heterogeneous results carry direct policy implications. The mobility penalty is nearly three times larger in districts with historically thin credit markets, establishing that improved household liquidity during prenatal and early childhood windows, through credit access, could substantially interrupt the intergenerational transmission of climatic damage. The penalty on female children is approximately double that on males in magnitude, suggesting the Heat Trap is a gendered force that standard aggregate estimates systematically understate.

Standard estimates of the economic cost of warming focus on contemporaneous productivity and omit the forward tax that heat imposes on the human capital of children not yet born. The districts of India that will warm most in coming decades are, by and large, those with the thinnest credit markets, the highest rates of agricultural employment, and the weakest historical infrastructure for human capital investment. The Heat Trap is not a metaphor but a mechanism: a self reinforcing interaction between environmental stress, biological vulnerability, and institutional scarcity that will quietly compress the intergenerational mobility of hundreds of millions of families whose children have not yet been born.

9 Figures

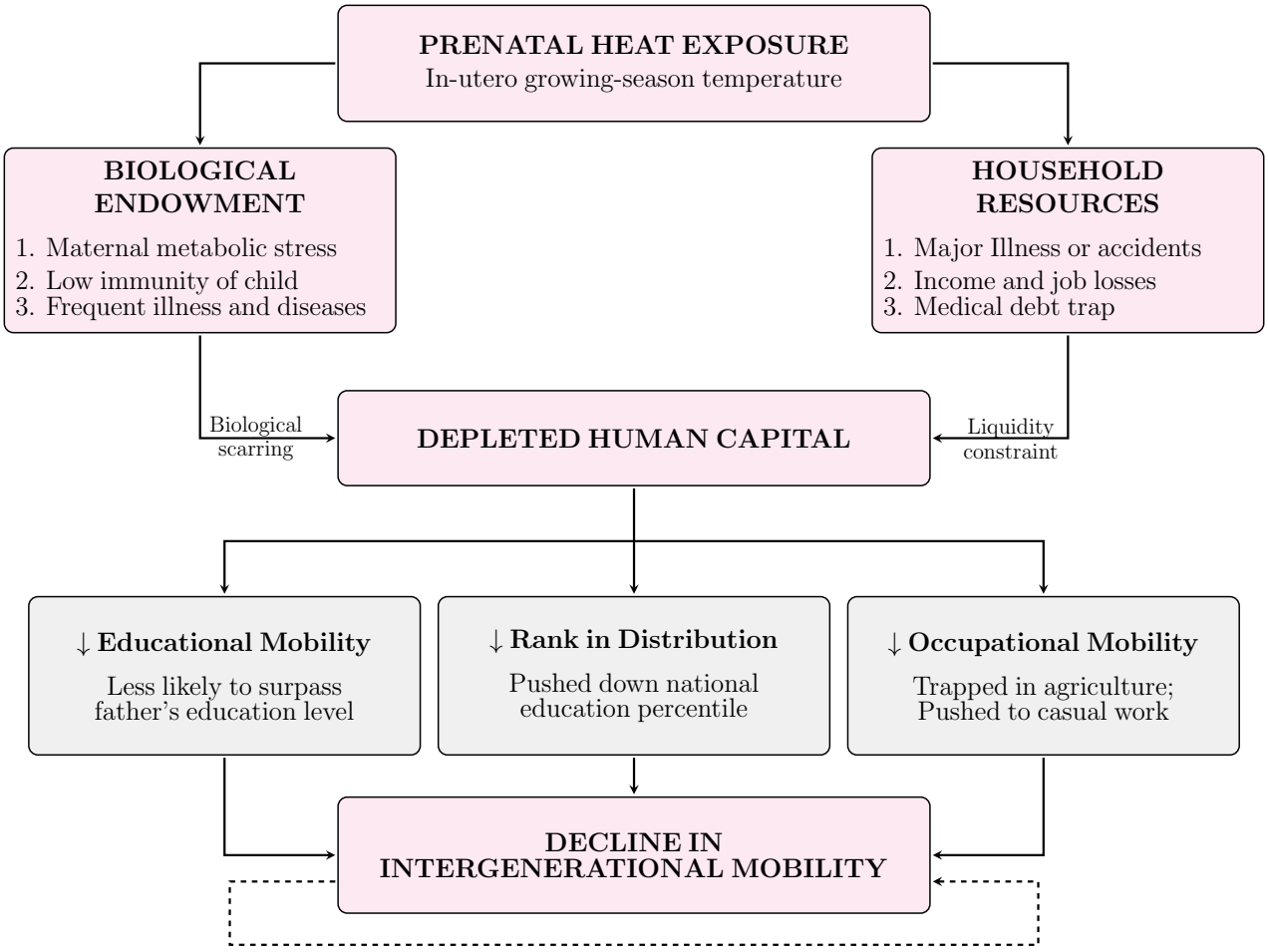
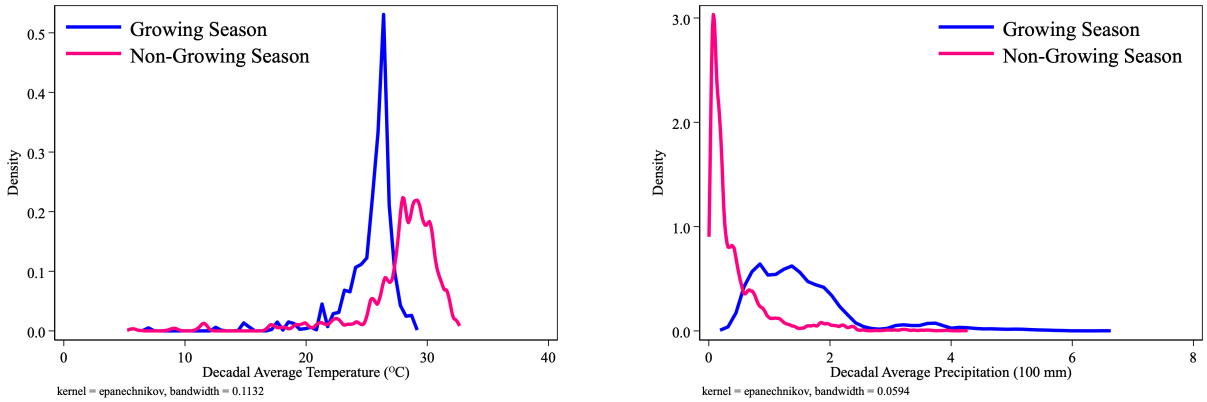


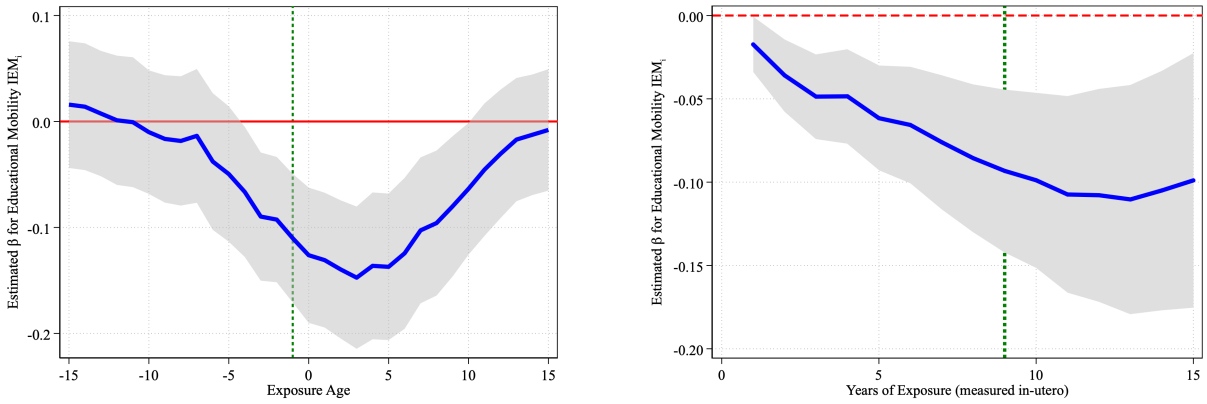
Figure 1: Conceptual Framework



A: *Temperature (°C)*

B: *Precipitation (100 mm)*

Figure 2: Density Plots for In-utero Weather
Figure shows the distribution of in-utero exposure to average decadal temperature (Panel A) and precipitation (Panel B). We construct density plots using epanechnikov kernels.



A: *Impact of Average Decadal GS Temperature across different Exposure Age*

B: *Impact of Average GS Temperature across different Years of (In-Utero) Exposure*

Figure 3: Relationship between Growing Season (GS) Temperature and Intergenerational Educational Mobility IEM_i: Role of Timing and Intensity of Exposure
Figure shows the estimated β coefficient between growing season temperature (°C) and Intergenerational Educational Mobility (IEM_i), a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021), using information from the Individual Module of IHDS 2011-12 survey. We implement our baseline specification (Equation 1) for varying age of exposure (Panel A) and varying amount of in-utero exposure (Panel B). All the estimations control for growing season precipitation (100 mm), weather in the non-growing seasons, fixed effects for district, birth year, and birth month, region-specific linear trends in birth year, and standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for caste and religion of the household). The vertical dotted green lines show our baseline estimates (Table 2, Panel A, Column 4). The 95% confidence bands have been constructed using robust standard errors clustered at the district level.

10 Tables

Table 1: Summary Statistics

	N	Mean	SD	Min	P25	P50	P75	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Child-Father Matched Data (IHDS 2011-12 Individual Module)								
Demographics								
Male	129351	0.49	0.50	0	0	0	1	1
Age (years)	129351	34.16	13.06	15	23	32	45	62
Married	129349	0.68	0.47	0	0	1	1	1
Brahmins	129063	0.05	0.22	0	0	0	0	1
Forward Castes / Others	129063	0.25	0.43	0	0	0	0	1
Other Backward Castes (OBC)	129063	0.41	0.49	0	0	0	1	1
Scheduled Castes (SC)	129063	0.21	0.41	0	0	0	0	1
Scheduled Tribes (ST)	129063	0.08	0.28	0	0	0	0	1
Household in Urban Residence	129351	0.36	0.48	0	0	0	1	1
Education								
Child's Education Level	129178	6.40	4.79	0	2	8	10	14
Father's Education Level	103602	3.83	4.49	0	0	2	8	14
Child completed Primary School	129178	0.68	0.47	0	0	1	1	1
Child completed Elementary School	129178	0.52	0.50	0	0	1	1	1
Child completed High School	129178	0.34	0.47	0	0	0	1	1
Child completed University	129178	0.10	0.30	0	0	0	0	1
Intergenerational Educational Mobility IEM_i	103510	0.57	0.50	0	0	1	1	1
Child's Education Rank	129178	51.09	27.92	1.87	24.47	50.93	76.42	99.99
Father's Education Rank (Among Children)	103510	50.49	26.87	15.21	25.94	44.74	75.11	99.03
Bottom Quartile Upper-Half Mobility	103510	0.06	0.23	0	0	0	0	1
Child engaged in Agricultural Occupation	50340	0.30	0.46	0	0	0	1	1
Child engaged in Blue Collar Occupation	50340	0.56	0.50	0	0	1	1	1
Child engaged in White Collar Occupation	50340	0.14	0.35	0	0	0	0	1
Intergenerational Educational Mobility IEM_i	103510	0.57	0.50	0	0	1	1	1
Occupation								
Child engaged in Agricultural Occupation	50340	0.30	0.46	0	0	0	1	1
Child engaged in Blue Collar Occupation	50340	0.56	0.50	0	0	1	1	1
Child engaged in White Collar Occupation	50340	0.14	0.35	0	0	0	0	1
Father engaged in Agricultural Occupation	127918	0.62	0.49	0	0	1	1	1
Father engaged in Blue Collar Occupation	127918	0.30	0.46	0	0	0	1	1
Father engaged in White Collar Occupation	127918	0.08	0.27	0	0	0	0	1
Intergenerational Occupational Mobility IOM_i	49845	0.42	0.49	0	0	0	1	1
Mobility towards Non-Agricultural Occupations	49845	0.38	0.48	0	0	0	1	1
Human Capital Intensity based Occupational Mobility	49845	0.65	0.48	0	0	1	1	1
B: Household Losses (IHDS 2011-12 Household Module)								
Household Loss Index	41520	0.00	0.54	-0.35	-0.30	-0.30	0.26	4.36
Loss due to Major Illness / Accidents	41510	0.27	0.44	0	0	0	1	1
Drought, Flood, or Fire related Loss	41519	0.08	0.27	0	0	0	0	1
Loss of Job	41514	0.03	0.16	0	0	0	0	1
Other Economic Loss	41256	0.02	0.15	0	0	0	0	1
Loan for Medical Expenditure	41588	0.08	0.28	0	0	0	0	1
C: Health Characteristics (NFHS 2015-16 Child and Women Module)								
Maternal Health								
Metabolic Syndrome Index	436469	0.00	0.55	-0.21	-0.21	-0.21	-0.21	7.43
High Blood Pressure	430451	0.11	0.31	0	0	0	0	1
Diabetes	436469	0.02	0.13	0	0	0	0	1
Heart Disease	436469	0.02	0.13	0	0	0	0	1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Obesity	430341	0.05	0.23	0	0	0	0	1
Asthma	434401	0.02	0.14	0	0	0	0	1
Child Health								
Anemia	138751	0.32	0.47	0	0	0	1	1
Delay in Breastfeeding	164205	0.68	0.69	0	0	1	1	2
Diarrhea	168618	0.21	0.61	0	0	0	0	2
Fever in last two weeks	168651	0.15	0.35	0	0	0	0	1
D: District Characteristics (Weather Data)								
In-Utero Exposure to Weather								
10-Year Average GS Temperature (°C)	129351	25.26	2.41	6.64	24.71	25.98	26.49	29.05
10-Year Average NGS Temperature (°C)	129351	27.87	3.54	5.23	27.25	28.64	29.86	32.66
10-Year Average GS Precipitation (100 mm)	129351	1.56	0.92	0.25	0.92	1.37	1.86	6.58
10-Year Average NGS Precipitation (100 mm)	129351	0.42	0.54	0.00	0.10	0.21	0.50	4.27
10-Year Average GS Rainfall Shock	129349	0.00	0.64	-1	0	0	0	1
10-Year Average NGS Rainfall Shock	129349	0.08	0.64	-1	0	0	0	1
10-Year Average GS Positive Rainfall Shock	129349	0.19	0.39	0	0	0	0	1
10-Year Average GS Negative Rainfall Shock	129349	0.23	0.42	0	0	0	0	1
10-Year Average NGS Positive Rainfall Shock	129349	0.22	0.42	0	0	0	0	1
10-Year Average NGS Negative Rainfall Shock	129349	0.19	0.39	0	0	0	0	1

Table 2: Impact of In-Utero Exposure to Growing Season Temperature on Upward Educational Mobility

	(1)	(2)	(3)	(4)
A. Intergenerational Educational Mobility				
GS Temperature (°C)	-0.127***	-0.113***	-0.105***	-0.093***
	(0.033)	(0.026)	(0.024)	(0.025)
GS Precipitation (100mm)	-0.004	-0.001	-0.008	-0.010
	(0.020)	(0.015)	(0.014)	(0.015)
Outcome Mean	0.566	0.566	0.566	0.566
Observations	103157	101885	101885	101885
Adjusted$-R^2$	0.065	0.233	0.237	0.235
B. Child's Education Rank				
GS Temperature (°C)	-5.473***	-5.619***	-3.261***	-3.292***
	(1.382)	(1.329)	(1.146)	(1.237)
GS Precipitation (100mm)	0.360	1.010	0.598	0.324
	(0.958)	(0.832)	(0.832)	(0.826)
Outcome Mean	51.126	51.965	51.965	51.965
Observations	128763	101885	101885	101885
Adjusted$-R^2$	0.141	0.376	0.381	0.380
C. Bottom Quartile Upper-Half Mobility				
GS Temperature (°C)	-0.057***	-0.059***	-0.021*	-0.031**
	(0.014)	(0.014)	(0.012)	(0.013)
GS Precipitation (100mm)	-0.001	-0.002	0.002	-0.005
	(0.010)	(0.010)	(0.009)	(0.011)
Outcome Mean	0.058	0.058	0.058	0.058
Observations	103157	101885	101885	101885
Adjusted$-R^2$	0.087	0.188	0.197	0.192
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
State Birth Year Trends			✓	
Region Birth Year Trends				✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Upward Mobility in Education for individuals aged 15-60 years, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. Panel A shows Intergenerational Educational Mobility, a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). Panel B captures the education rank of the individuals, for whom we account for their fathers' education rank (Asher, Novosad, and Rafkin, 2024). Panel C shows the likelihood of Bottom Quartile Upper-Half Mobility using a binary indicator equal to one if the individual is in the upper half of the education distribution, conditional on fathers in the bottom quartile of their respective education distribution (Corak and Heisz, 1999; Acciari, Polo, and Violante, 2022). The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, and birth month in all specifications, we progressively account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), followed by state- or region-specific linear trends in birth year. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Impact of In-Utero Exposure to Growing Season Temperature on Upward Occupational Mobility

	(1)	(2)	(3)	(4)
A. Intergenerational Occupational Mobility				
GS Temperature (°C)	-0.083***	-0.055***	-0.046**	-0.050**
	(0.024)	(0.021)	(0.022)	(0.020)
GS Precipitation (100mm)	0.002	0.018	-0.003	0.005
	(0.022)	(0.015)	(0.015)	(0.014)
Outcome Mean	0.420	0.427	0.427	0.427
Observations	49701	42278	42278	42278
Adjusted$-R^2$	0.089	0.388	0.390	0.389
B. Mobility towards Non-Agricultural Occupations				
GS Temperature (°C)	-0.077***	-0.041**	-0.035*	-0.040**
	(0.023)	(0.019)	(0.019)	(0.018)
GS Precipitation (100mm)	-0.013	0.001	-0.014	-0.010
	(0.020)	(0.012)	(0.012)	(0.012)
Outcome Mean	0.377	0.385	0.385	0.385
Observations	49701	42278	42278	42278
Adjusted$-R^2$	0.089	0.492	0.493	0.493
C. Human Capital Intensity based Occupational Mobility				
GS Temperature (°C)	-0.042**	-0.048**	-0.041*	-0.048**
	(0.021)	(0.021)	(0.023)	(0.021)
GS Precipitation (100mm)	0.010	0.011	-0.006	-0.003
	(0.013)	(0.013)	(0.014)	(0.013)
Outcome Mean	0.647	0.653	0.653	0.653
Observations	49701	42278	42278	42278
Adjusted$-R^2$	0.186	0.279	0.280	0.280
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
State Birth Year Trends			✓	
Region Birth Year Trends				✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Upward Mobility in Occupation for individuals aged 15-60 years, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. Panel A shows Intergenerational Occupational Mobility, a level based binary indicator constructed by comparing the occupation categories of children with their fathers (Alesina et al., 2021). Panel B shows Mobility towards Non-Agricultural Occupations, a binary outcome equal to one if an individual is engaged in a Non-Agricultural Occupation, and his father is engaged in an Agricultural Occupation. In Panel C, we follow Brahma (2025) and Ahsan and Chatterjee (2017) and compute human capital score for each occupation as per the National Classification of Occupations (NCO) 1968, and construct a binary indicator for upward mobility, that takes a value equal to one if a child is working in an occupation that has a human capital score higher than that of his/her father. The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into three mutually exclusive categories: White collar, Blue collar, and Agricultural occupations. The white collar category includes professionals, administrative and managerial workers, and clerical workers. Blue collar occupations comprise sales and service workers along with production, transport, and other manual occupations. Agricultural occupations are identified as farm managers, cultivators, agricultural laborers, and workers in fishing and forestry. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, and birth month in all specifications, we progressively account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), followed by state- or region-specific linear trends in birth year. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Impact of In-Utero Exposure to Growing Season Temperature on Completion of Educational Levels and Occupational Choices of Individuals

A. Educational Levels	**Primary School**	**Elementary School**	**High School**	**University**
	(1)	(2)	(3)	(4)
GS Temperature (°C)	-0.060***	-0.092***	-0.039**	-0.048***
	(0.021)	(0.022)	(0.019)	(0.013)
GS Precipitation (100mm)	-0.004	-0.009	0.004	0.006
	(0.014)	(0.014)	(0.015)	(0.011)
Outcome Mean	0.710	0.547	0.356	0.103
Observations	101885	101885	101885	101885
Adjusted$-R^2$	0.304	0.331	0.312	0.200
B. Occupational Choices	**Agricultural Occupation**	**Blue Collar Occupation**	**White Collar Occupation**	**Casual Work**
	(1)	(2)	(3)	(4)
GS Temperature (°C)	0.040*	-0.037	-0.003	0.043**
	(0.023)	(0.027)	(0.019)	(0.021)
GS Precipitation (100mm)	0.006	-0.015	0.009	-0.006
	(0.014)	(0.017)	(0.013)	(0.013)
Outcome Mean	0.293	0.565	0.143	0.741
Observations	42278	42278	42278	42461
Adjusted$-R^2$	0.330	0.217	0.241	0.280
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
State Birth Year Trends	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on completion of Education levels, and Occupational choices of individuals, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. Panel A shows binary outcomes for completion of Primary, Elementary, High School and University. Panel B shows binary outcomes for Agricultural, Blue. Collar, White Collar Occupations and Casual Work. The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into the three mutually exclusive categories. The white collar category includes professionals, administrative and managerial workers, and clerical workers. Blue collar occupations comprise sales and service workers along with production, transport, and other manual occupations. Agricultural occupations are identified as farm managers, cultivators, agricultural laborers, and workers in fishing and forestry. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force. Casual Work is a binary indicator equal to one if the individual is working in a casual occupation, and zero for regular and/or permanent job. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, birth month, and state-specific linear trends in birth year, all specifications account for standard demographics, including gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Impact of Exposure to Growing Season Temperature on Household Losses

	Household Loss Index	**Major Illness or Accidents**	**Drought, Flood or Fire**	**Loss of Job**	**Other Economic Loss**	**Medical Loan**
	(1)	(2)	(3)	(4)	(5)	(6)
GS Temperature (°C)	0.073***	0.018**	0.021**	0.020***	0.007*	0.010***
	(0.016)	(0.009)	(0.009)	(0.006)	(0.004)	(0.002)
GS Precipitation (100mm)	-0.008	-0.015	0.004	-0.002	-0.001	0.002
	(0.018)	(0.013)	(0.007)	(0.004)	(0.007)	(0.002)
Region FE	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓	✓	✓
Outcome Mean	0.001	0.262	0.083	0.027	0.024	0.083
Observations	34875	34867	34874	34872	34645	34919
Adjusted$-R^2$	0.057	0.042	0.100	0.043	0.011	0.112

Notes: Table reports the impact of Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on outcomes indicating Household reported losses, constructed from the Household Module of IHDS 2011-12 survey. Column 1 shows the first outcome, Household Loss Index, constructed by averaging standardized z-scores of loss due to major illness or accidents, drought, flood or fire related losses, loss of job, and other economic losses (Hoynes, Schanzenbach, and Almond, 2016). Columns 2 to 5 show the indicators for the four components as binary variables, each showing Major Illness / Accidents; Drought, Flood or Fire; Loss of Job; and Other Economic Loss respectively. Column 6 shows Medical Loan, a binary variable equal to one if the household has taken a loan for medical expenditure. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for region zones (Central, East, North, South, North-East, and West), all specifications account for household demographics, including age of male head, highest years of education of male and female adults, years stayed in the current place, total household assets owned, binary indicators for ownership of land, ownership of nonfarm business, outstanding debt in the last five years, BPL card ownership, urban residence, poverty status, and fixed effects for caste, religion, and main source of income. Robust standard errors clustered at the district level are reported in parentheses.

Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Impact of Exposure (during Pregnancy) to Growing Season Temperature on Mother's Health

	Metabolic Syndrome Index	**High Blood Pressure**	**Diabetes**	**Heart Disease**	**Obesity**	**Asthma**
	(1)	(2)	(3)	(4)	(5)	(6)
GS Temperature (°C)	0.027***	0.010***	0.003***	0.003***	0.007***	0.002**
	(0.005)	(0.004)	(0.001)	(0.001)	(0.002)	(0.001)
GS Precipitation (100mm)	0.005	0.009**	0.002*	-0.001	-0.003	-0.001
	(0.006)	(0.005)	(0.001)	(0.001)	(0.002)	(0.001)
State FE	✓	✓	✓	✓	✓	✓
Mother Birth Year FE	✓	✓	✓	✓	✓	✓
Mother Birth Month FE	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
State Birth Year Trends	✓	✓	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓	✓	✓
Outcome Mean	0.003	0.108	0.018	0.018	0.055	0.020
Observations	415460	409664	415460	415460	409557	413512
Adjusted$-R^2$	0.071	0.046	0.023	0.010	0.056	0.008

Notes: Table reports the impact of Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) during pregnancy on mother's health outcomes constructed from the 2015-16 National Family Health Survey (NFHS-4) of India. Column 1 shows the first outcome, Metabolic Syndrome Index, constructed by averaging standardized z-scores of high blood pressure, diabetes, heart disease, and obesity (Hoynes, Schanzenbach, and Almond, 2016). Columns 2 to 4 show the indicators for the four components as binary variables: the first three showing whether the mother was diagnosed with high blood pressure, diabetes, and heart disease respectively. The fourth component, Obesity, is a binary indicator equal to one if the body mass index is greater than or equal to 30 kg/m^2 (Sekhri and Shastry, 2024; Singh et al., 2025). Column 6 shows whether the mother was diagnosed with asthma. The sample excludes all pregnant women and those smoking cigarettes (Dasgupta, Majid, and Orman, 2023), although our results are not driven by this restriction. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for state, mother birth year, mother birth month, and state-specific linear trends in mother birth year, all specifications account for the age of mother, and include fixed effects for education levels of mother, and wealth quintiles, urban residence, religion and social group of the household. To address migration-related concerns, we control for the number of years, the mother has stayed in the current place of residence (Dasgupta, Majid, and Orman, 2023). Robust standard errors clustered at the district level are reported in parentheses.

Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Impact of In-Utero Exposure to Growing Season Temperature on Child's Health

	(1) Size at Birth	(2) Low Birth Weight	(3) Delay in Breastfeeding	(4) Diarrhea
GS Temperature (°C)	-0.048**	0.054*	0.133***	0.222***
	(0.024)	(0.030)	(0.049)	(0.080)
GS Precipitation (100mm)	-0.048	0.045	0.065	0.114
	(0.030)	(0.040)	(0.049)	(0.072)
Outcome Mean	0.880	0.160	0.682	0.211
Observations	165247	128618	160865	168089
Adjusted$-R^2$	0.019	0.024	0.135	0.044
	Stunting	**Wasting**	**Underweight**	**Severe Anemia**
GS Temperature (°C)	0.242***	0.103*	0.217***	0.084**
	(0.061)	(0.062)	(0.057)	(0.039)
GS Precipitation (100mm)	0.015	-0.023	0.064	0.061**
	(0.064)	(0.069)	(0.079)	(0.029)
Outcome Mean	0.799	0.821	0.898	0.051
Observations	152773	153140	152773	138072
Adjusted$-R^2$	0.070	0.062	0.082	0.043
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
State Birth Year Trends	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) child's health outcomes constructed from the 2015-16 National Family Health Survey (NFHS-4) of India. The first outcome Size at Birth is a binary indicator equal to one if the child was of normal or large size at birth, and zero for small size. The second outcome Low Birth Weight is a binary indicator equal to one if the child had weight at birth less than 2500 grams, as defined by World Health Organization (2022), and zero otherwise. Delay in Breastfeeding is a categorical variable giving the time when the child was put into breastfeeding, ranging from immediately to days. Diarrhea is a binary outcome equal to one if the child experienced diarrhea recently, and zero otherwise. Stunting is defined as a height-for-age (HAZ) score of less than -2 standard deviations. Wasting is defined as a weight-for-height (WHZ) score of less than -2 standard deviations. Underweight is defined as a weight-for-age (WAZ) score of less than -2 standard deviations. These child malnutrition binary indicators have been constructed based on z-scores, according to the reference manual on child growth standards outlined by World Health Organization (2006). Severe Anemia is a binary outcome equal to one if the hemoglobin (Hg) level of the child is below 80 g/L, and zero otherwise, based on WHO guidelines (USAID, 2017). The sample for this particular outcome excludes outliers in hemoglobin, and includes children satisfying ($Hg \in (40, 180)$). The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, child birth year, child birth month, and state-specific linear trends in child birth year, all specifications account for the age of mother and her child, gender of child, number of children aged 5 years and below in the household, and include fixed effects for birth order of the children, and wealth quintiles, urban residence, religion and social group of the household. The regression for Delay in Breastfeeding substitutes the fixed effects and trends of birth year and month of the child with those of their mother. To address migration-related concerns, we control for the number of years, the mother has stayed in the current place of residence (Dasgupta, Majid, and Orman, 2023). Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Education: Mediation by Major Health Morbidity

	Intergenerational Educational Mobility	**Child's Education Rank**	**Bottom Quartile Upper-Half Mobility**
	(1)	(2)	(3)
Major $\widehat{\text{Health}}$ Morbidity	-0.186***	-9.992***	-0.069***
	(0.016)	(0.984)	(0.005)
GS Temperature (°C)	-0.051*	2.048	0.006
	(0.031)	(1.365)	(0.012)
GS Precipitation (100mm)	-0.030*	-0.142	-0.006
	(0.016)	(0.937)	(0.009)
District FE	✓	✓	✓
Birth Year FE	✓	✓	✓
Birth Month FE	✓	✓	✓
Demographic Controls	✓	✓	✓
State Birth Year Trends	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓
Outcome Mean	0.566	51.965	0.058
Observations	101885	101885	101885
Adjusted$-R^2$	0.237	0.383	0.197

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Upward Mobility in Education for individuals aged 15-60 years, mediated by Major Health Morbidity, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. The first outcome Intergenerational Educational Mobility is a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). The second outcome Child's Education Rank captures the education rank of the individuals, for whom we account for their fathers' education rank (Asher, Novosad, and Rafkin, 2024). The third outcome shows the likelihood of Bottom Quartile Upper-Half Mobility using a binary indicator equal to one if the individual is in the upper half of the education distribution, conditional on fathers in the bottom quartile of their respective education distribution (Corak and Heisz, 1999; Acciari, Polo, and Violante, 2022). Major Health Morbidity captures the standardized predicted impact of in-utero exposure to temperature and precipitation (separated by seasons) in a first-stage regression, accounting for standard demographics (age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), fixed effects for district, birth year, birth month, and state-specific linear trends in birth year. *Major Health Morbidity* is a binary indicator that takes a value equal to one if an individual has a major morbidity (among fourteen major problems including high blood pressure, heart disease, diabetes, cancer, asthma, and others), and zero otherwise. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. In the second-stage specifications, we include the standardized predicted major health morbidity, age and age squared of individual, and introduce fixed effects for district, birth year, birth month, and state-specific linear trends in birth year. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Impact of In-Utero Exposure to Growing Season Temperature on Upward Educational Mobility: Heterogeneity across Household Demographics

	(1)	(2)	(3)	(4)	(5)
GS Temperature (°C)	-0.117***	-0.099***	-0.100***	-0.094***	-0.101***
	(0.029)	(0.025)	(0.024)	(0.024)	(0.024)
GS Precipitation (100mm)	-0.012	-0.007	-0.008	-0.006	-0.004
	(0.017)	(0.015)	(0.015)	(0.015)	(0.015)
GS Temperature (°C) × Educated Fathers	-0.021***				
	(0.006)				
GS Precipitation (100mm) × Educated Fathers	-0.004				
	(0.009)				
GS Temperature (°C) × Non-Agricultural Fathers		-0.017***			
		(0.004)			
GS Precipitation (100mm) × Non-Agricultural Fathers		-0.004			
		(0.005)			
GS Temperature (°C) × Muslim Households			-0.038***		
			(0.008)		
GS Precipitation (100mm) × Muslim Households			-0.006		
			(0.012)		
GS Temperature (°C) × Male Individuals				-0.008	
				(0.006)	
GS Precipitation (100mm) × Male Individuals				-0.004	
				(0.008)	
GS Temperature (°C) × Urban Residence					-0.011
					(0.007)
GS Precipitation (100mm) × Urban Residence					-0.009
					(0.009)
District FE	✓	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓
State Birth Year Trends	✓	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓	✓
Outcome Mean	0.566	0.566	0.566	0.566	0.566
Observations	101887	101887	101887	101887	101887
Adjusted$-R^2$	0.129	0.233	0.237	0.240	0.243

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Intergenerational Educational Mobility (IEM) across various household demographic characteristics, for individuals aged 15-60 years, constructed from the Individual Module of IHDS 2011-12 survey. The outcome is a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). We augment our baseline specifications (Columns 3, using state-specific linear trends in birth year) from Table 2 by allowing for variation in the net effects of temperature and precipitation across Educated vs Uneducated Fathers, Non-Agricultural vs Agricultural Fathers, Muslim vs Non-Muslim households, Males vs Females, and households living in Urban vs Rural areas. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, birth month, and state-specific linear trends in birth year, we account for standard demographics (gender, age, and age squared of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household). Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Impact of In-Utero Exposure to Growing Season Temperature on Upward Educational Mobility: Heterogeneity across District-level Institutions

	(1)	(2)	(3)	(4)	(5)
GS Temperature (°C)	-0.102***	-0.101***	-0.099***	-0.105***	-0.114***
	(0.025)	(0.026)	(0.025)	(0.026)	(0.026)
GS Precipitation (100mm)	-0.011	-0.018	-0.003	-0.014	-0.013
	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)
GS Temperature (°C) × High Bank Density	-0.006				
	(0.011)				
GS Precipitation (100mm) × High Bank Density	0.005				
	(0.012)				
GS Temperature (°C) × High Health Infrastructure		-0.009			
		(0.013)			
GS Precipitation (100mm) × High Health Infrastructure		0.021			
		(0.017)			
GS Temperature (°C) × High Government Expenditure			-0.014		
			(0.010)		
GS Precipitation (100mm) × High Government Expenditure			-0.016		
			(0.015)		
GS Temperature (°C) × High Electricity Infrastructure				0.002	
				(0.010)	
GS Precipitation (100mm) × High Electricity Infrastructure				0.014	
				(0.010)	
GS Temperature (°C) × High Irrigated Land					0.019
					(0.014)
GS Precipitation (100mm) × High Irrigated Land					0.010
					(0.025)
District FE	✓	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓
State Birth Year Trends	✓	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓	✓
Outcome Mean	0.566	0.566	0.566	0.566	0.566
Observations	101887	101887	101887	101887	101887
Adjusted$-R^2$	0.237	0.237	0.237	0.237	0.237

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Intergenerational Educational Mobility (IEM) across various household demographic characteristics, for individuals aged 15-60 years, constructed from the Individual Module of IHDS 2011-12 survey. The outcome is a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). We augment our baseline specifications (Columns 3, using state-specific linear trends in birth year) from Table 2 by allowing for variation in the net effects of temperature and precipitation across different institutional dimensions, which we construct on the basis of median of capacity as of 2001 Population Census. These include number of banks; number of hospitals, dispensaries, clinics, health centres, etc.; government spending on public administration, safety, health, works, etc.; total domestic, industrial, commercial, and road lighting electrical connections; and total irrigated land in rural areas in the districts. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, birth month, and state-specific linear trends in birth year, we account for standard demographics (gender, age, and age squared of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household). Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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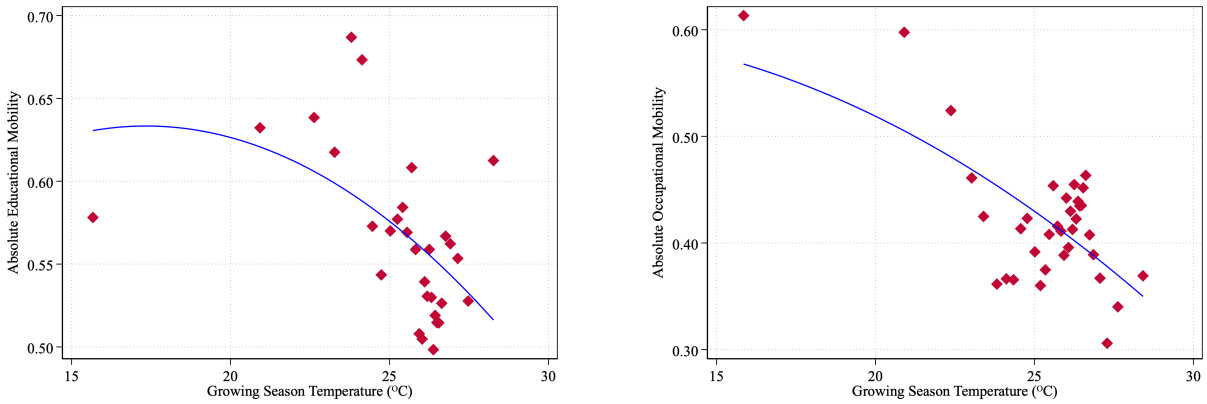
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APPENDIX

A Appendix Figures

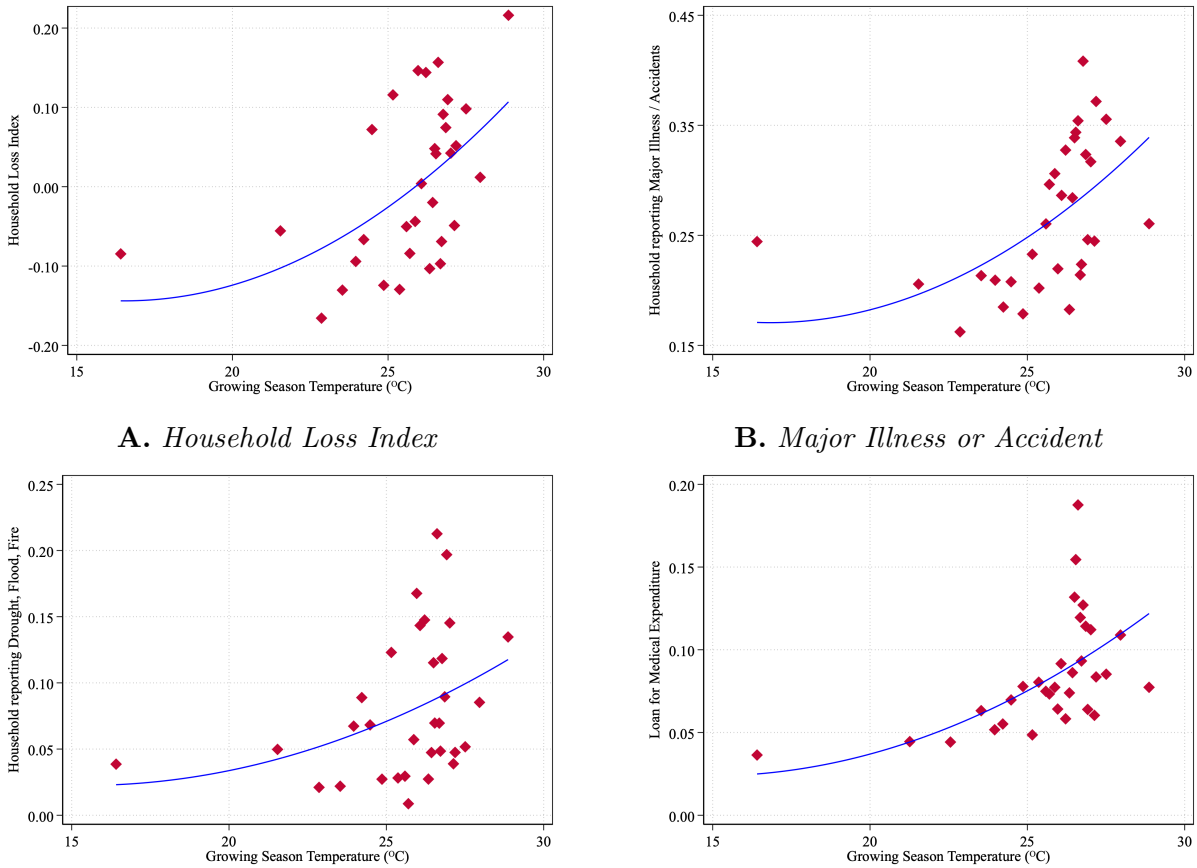


A: *Educational Mobility* IEM_i

B: *Occupational Mobility* IOM_i

Figure B1: Unconditional Correlations: Intergenerational Upward Mobility and In-Utero Exposure to Growing Season Temperature

Figure shows the unconditional correlations between intergenerational upward mobility in education (Panel A: IEM_i) and occupation (Panel B: IOM_i) and in-utero exposure to average decadal temperature (°C) in the growing season. The mobility metrics have been constructed for individuals aged 15-60 years from the Individual Module of the India Human Development Survey (IHDS) 2011-12. Intergenerational Educational Mobility is a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). Intergenerational Occupational Mobility is a level based binary indicator constructed by comparing the occupation categories of children with their fathers (Alesina et al., 2021). The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into three mutually exclusive categories: White collar, Blue collar, and Agricultural occupations. The white collar category includes professionals, administrative and managerial workers, and clerical workers. Blue collar occupations comprise sales and service workers along with production, transport, and other manual occupations. Agricultural occupations are identified as farm managers, cultivators, agricultural laborers, and workers in fishing and forestry. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force.



A. *Household Loss Index*

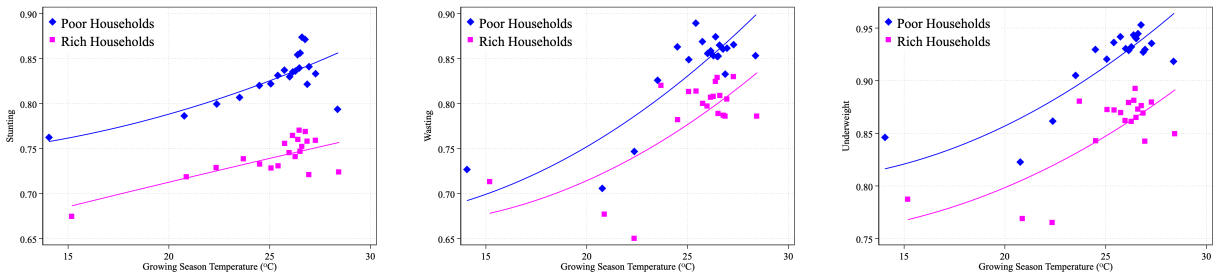
B. *Major Illness or Accident*

C. *Drought, Flood or Fire related Loss*

D. *Loan for Medical Expenditure*

Figure B2: Unconditional Correlations: Household reported Losses and Exposure to Growing Season Temperature

Figure shows the unconditional correlations between household reported losses and exposure to average decadal temperature (°C) in the growing season. Panel A shows Household Loss Index constructed by averaging the standardized z-scores of loss due to major illness or accident; drought, flood, or fire; loss of job; and other economic losses (Hoynes, Schanzenbach, and Almond, 2016). Panels B and C show the individual components: loss due to major illness or accident; and drought, flood, or fire respectively. Panel D shows Loan taken by the household for medical expenditure. The outcomes have been constructed from the Household Module of the India Human Development Survey (IHDS) 2011-12.



A: *Stunting* **B:** *Wasting* **C:** *Underweight*

Figure B3: Unconditional Correlations: Child Malnutrition and In-Utero Exposure to Growing Season Temperature

Figure shows the unconditional correlations between child malnutrition indicators and in-utero exposure to average decadal temperature (°C) in the growing season, disaggregated by children belonging to poor and rich households. Following the guidelines on child growth standards outlined by World Health Organization (2006), we construct these binary indicators based on z-scores available in the National Family Health Survey (NFHS) conducted in 2015-2016. These include: *Stunting*, defined as a height-for-age (HAZ) score of less than -2 standard deviations; *Wasting*, defined as a weight-for-height (WHZ) score of less than -2 standard deviations; and *Underweight*, defined as a weight-for-age (WAZ) score of less than -2 standard deviations. We distinguish between poor and rich households using a binary indicator equal to one if a household is classified as richer or richest in the wealth quintiles, and zero otherwise.

B Appendix Tables

Table B1: Impact of In-utero Exposure to Growing Season Temperature on Infant and Neo-natal Mortality

	Infant Mortality		**Neo-natal Mortality**	
	(1)	(2)	(3)	(4)
GS Temperature (°C)	0.010***	0.010***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
GS Precipitation (100mm)	0.018***	0.018***	0.015***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
GS Temperature (°C) × Wealthy Household		0.000		0.000
		(0.000)		(0.000)
GS Precipitation (100mm) × Wealthy Household		-0.000		-0.000
		(0.001)		(0.001)
District FE	✓	✓	✓	✓
Mother Birth Year FE	✓	✓	✓	✓
Mother Birth Month FE	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
State Birth Year Trends	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓
Outcome Mean	0.024	0.024	0.018	0.018
Observations	435141	435141	435141	435141
Adjusted$-R^2$	0.010	0.010	0.008	0.008

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Infant and Neo-Natal Mortality constructed from the 2015-16 National Family Health Survey (NFHS-4) of India. The first outcome Infant Mortality is a binary indicator equal to one if the child died within 12 months of birth, and zero otherwise. The second outcome Neo-natal Mortality is a binary indicator equal to one if the child died within 28 days of birth, and zero otherwise. Columns 1 and 3 show the baseline specifications, and Columns 2 and 4 augment them by allowing for variation in the net effects of temperature and precipitation across Wealthy and Non-Wealthy households, respectively. Following Liu, Shamdasani, and Taraz (2023), we interact the weather variables with *Wealthy Household*, a binary indicator equal to one if a household is classified as richer or richest in the wealth quintiles, and zero otherwise. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, mother birth year, mother birth month, and state-specific linear trends in mother birth year, all specifications account for the age of mother, and include fixed effects for birth order of children, education levels of mother, and urban residence, religion and social group of the household. To address migration-related concerns, we control for the number of years, the mother has stayed in the current place of residence (Dasgupta, Majid, and Orman, 2023). Robust standard errors clustered at the district level are reported in parentheses.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Impact of In-utero Exposure to Growing Season Temperature on Fertility and Composition of Births

	Births in Past Year	**Girl Child Born**				
	(1)	(2)	(3)	(4)	(5)	(6)
		1^{st} *Child*	2^{nd} *Child*	3^{rd} *Child*	4^{th} *Child*	5^{th} *Child*
GS Temperature (°C)	0.004	-0.001	0.000	-0.002	-0.002	-0.004
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
GS Precipitation (100mm)	0.025***	0.004	0.009**	0.014***	0.014*	0.033***
	(0.007)	(0.003)	(0.005)	(0.005)	(0.009)	(0.012)
State FE	✓	✓	✓	✓	✓	✓
Mother Birth Year FE	✓					
Mother Birth Month FE	✓					
Child Birth Year FE		✓	✓	✓	✓	✓
Child Birth Month FE		✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
State Birth Year Trends	✓	✓	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓	✓	✓
Outcome Mean	0.114	0.434	0.409	0.399	0.412	0.427
Observations	435141	85236	144552	97641	53874	27282
Adjusted$-R^2$	0.219	0.021	0.017	0.012	0.009	0.009

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Fertility and Composition of births constructed from the 2015-16 National Family Health Survey (NFHS-4) of India. The first outcome shows the Number of births in the previous year of the survey. The second outcome is a binary indicator, that takes a value of one if the mother gave birth to a girl child, and zero otherwise. We examine the composition of births according to the birth order. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for state, birth year, birth month, and state-specific linear trends in respective birth year(s), we account for the age of mother, and include fixed effects for urban residence, religion and social group of the household. To address migration-related concerns, we control for the number of years, the mother has stayed in the current place of residence (Dasgupta, Majid, and Orman, 2023). Robust standard errors clustered at the district level are reported in parentheses.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3: Impact of In-Utero Exposure to Growing Season Temperature on Upward Educational Mobility: Two-Way Clustering by District and Birth Year

	(1)	(2)	(3)	(4)
A. Intergenerational Educational Mobility				
GS Temperature (°C)	-0.127***	-0.113***	-0.105***	-0.093***
	(0.017)	(0.015)	(0.017)	(0.015)
GS Precipitation (100mm)	-0.004	-0.001	-0.008	-0.010
	(0.012)	(0.011)	(0.011)	(0.011)
Outcome Mean	0.566	0.566	0.566	0.566
Observations	103157	101885	101885	101885
Adjusted$-R^2$	0.065	0.233	0.237	0.235
B. Child's Education Rank				
GS Temperature (°C)	-5.473***	-5.619***	-3.261***	-3.292***
	(0.817)	(0.786)	(0.857)	(0.792)
GS Precipitation (100mm)	0.360	1.010*	0.598	0.324
	(0.580)	(0.543)	(0.560)	(0.537)
Outcome Mean	51.126	51.965	51.965	51.965
Observations	128763	101885	101885	101885
Adjusted$-R^2$	0.141	0.376	0.381	0.380
C. Bottom Quartile Upper-Half Mobility				
GS Temperature (°C)	-0.057***	-0.059***	-0.021***	-0.031***
	(0.007)	(0.007)	(0.008)	(0.007)
GS Precipitation (100mm)	-0.001	-0.002	0.002	-0.005
	(0.006)	(0.006)	(0.006)	(0.006)
Outcome Mean	0.058	0.058	0.058	0.058
Observations	103157	101885	101885	101885
Adjusted$-R^2$	0.087	0.188	0.197	0.192
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
State Birth Year Trends			✓	
Region Birth Year Trends				✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Upward Mobility in Education for individuals aged 15-60 years, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. Panel A shows Intergenerational Educational Mobility, a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). Panel B captures the education rank of the individuals, for whom we account for their fathers' education rank (Asher, Novosad, and Rafkin, 2024). Panel C shows the likelihood of Bottom Quartile Upper-Half Mobility using a binary indicator equal to one if the individual is in the upper half of the education distribution, conditional on fathers in the bottom quartile of their respective education distribution (Corak and Heisz, 1999; Acciari, Polo, and Violante, 2022). The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, and birth month in all specifications, we progressively account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), followed by state- or region-specific linear trends in birth year. Robust standard errors two-way clustered at district × birth year level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B4: Impact of In-Utero Exposure to Growing Season Temperature on Upward Occupational Mobility: Two-Way Clustering by District and Birth Year

	(1)	(2)	(3)	(4)
A. Intergenerational Occupational Mobility				
GS Temperature (°C)	-0.083***	-0.055***	-0.046**	-0.050***
	(0.021)	(0.018)	(0.021)	(0.019)
GS Precipitation (100mm)	0.002	0.018	-0.003	0.005
	(0.015)	(0.012)	(0.013)	(0.012)
Outcome Mean	0.420	0.427	0.427	0.427
Observations	49701	42278	42278	42278
Adjusted$-R^2$	0.089	0.388	0.390	0.389
B. Mobility towards Non-Agricultural Occupations				
GS Temperature (°C)	-0.077***	-0.041**	-0.035*	-0.040**
	(0.020)	(0.016)	(0.019)	(0.017)
GS Precipitation (100mm)	-0.013	0.001	-0.014	-0.010
	(0.014)	(0.011)	(0.012)	(0.011)
Outcome Mean	0.377	0.385	0.385	0.385
Observations	49701	42278	42278	42278
Adjusted$-R^2$	0.089	0.492	0.493	0.493
C. Human Capital Intensity based Occupational Mobility				
GS Temperature (°C)	-0.042**	-0.048**	-0.041*	-0.048**
	(0.018)	(0.019)	(0.022)	(0.020)
GS Precipitation (100mm)	0.010	0.011	-0.006	-0.003
	(0.013)	(0.013)	(0.015)	(0.013)
Outcome Mean	0.647	0.653	0.653	0.653
Observations	49701	42278	42278	42278
Adjusted$-R^2$	0.186	0.279	0.280	0.280
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
State Birth Year Trends			✓	
Region Birth Year Trends				✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Upward Mobility in Occupation for individuals aged 15-60 years, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. Panel A shows Intergenerational Occupational Mobility, a level based binary indicator constructed by comparing the occupation categories of children with their fathers (Alesina et al., 2021). Panel B shows Mobility towards Non-Agricultural Occupations, a binary outcome equal to one if an individual is engaged in a Non-Agricultural Occupation, and his father is engaged in an Agricultural Occupation. In Panel C, we follow Brahma (2025) and Ahsan and Chatterjee (2017) and compute human capital score for each occupation as per the National Classification of Occupations (NCO) 1968, and construct a binary indicator for upward mobility, that takes a value equal to one if a child is working in an occupation that has a human capital score higher than that of his/her father. The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into three mutually exclusive categories: White collar, Blue collar, and Agricultural occupations. The white collar category includes professionals, administrative and managerial workers, and clerical workers. Blue collar occupations comprise sales and service workers along with production, transport, and other manual occupations. Agricultural occupations are identified as farm managers, cultivators, agricultural laborers, and workers in fishing and forestry. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, and birth month in all specifications, we progressively account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), followed by state- or region-specific linear trends in birth year. Robust standard errors two-way clustered at district × birth year level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B5: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Education and Occupation: Logistic Regressions

	(1)	(2)	(3)	(4)
A. Educational Mobility IEM_i				
GS Temperature (°C)	-0.565***	-0.626***	-0.546***	-0.505***
	(0.140)	(0.122)	(0.129)	(0.121)
GS Precipitation (100mm)	0.003	0.019	-0.039	-0.042
	(0.083)	(0.077)	(0.079)	(0.078)
Outcome Mean	0.566	0.591	0.591	0.591
Observations	103155	97433	97433	97433
Pseudo$-R^2$	0.051	0.160	0.164	0.162
B. Occupational Mobility IOM_i				
GS Temperature (°C)	-0.381***	-0.390***	-0.311**	-0.343**
	(0.106)	(0.146)	(0.154)	(0.140)
GS Precipitation (100mm)	0.001	0.164	0.014	0.078
	(0.099)	(0.112)	(0.115)	(0.107)
Outcome Mean	0.420	0.457	0.457	0.457
Observations	49701	39444	39444	39444
Pseudo$-R^2$	0.073	0.328	0.331	0.330
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
State Birth Year Trends			✓	
Region Birth Year Trends				✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Absolute Upward Mobility in Education and Occupation for individuals aged 15-60 years, using Level based binary indicators, constructed by comparing the educational attainment levels and the occupational groups of children with their fathers respectively (Alesina et al., 2021), in a Logistic regression framework. The outcomes have been constructed from the Individual Module of IHDS 2011-12 survey. The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into three mutually exclusive categories: White collar, Blue collar, and Agricultural occupations. The white collar category includes professionals, administrative and managerial workers, and clerical workers. Blue collar occupations comprise sales and service workers along with production, transport, and other manual occupations. Agricultural occupations are identified as farm managers, cultivators, agricultural laborers, and workers in fishing and forestry. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, and birth month in all specifications, we progressively account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), followed by state- or region-specific linear trends in birth year. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B6: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Education and Occupation: Weighted Regressions

	(1)	(2)	(3)	(4)
A: Educational Mobility IEM_i				
GS Temperature (°C)	-0.155***	-0.129***	-0.122***	-0.097***
	(0.038)	(0.030)	(0.030)	(0.030)
GS Precipitation (100mm)	0.000	0.001	-0.017	-0.017
	(0.023)	(0.018)	(0.015)	(0.016)
Outcome Mean	0.566	0.566	0.566	0.566
Observations	103157	101885	101885	101885
Adjusted$-R^2$	0.069	0.231	0.236	0.234
B. Occupational Mobility IOM_i				
GS Temperature (°C)	-0.082***	-0.060**	-0.064**	-0.056**
	(0.030)	(0.027)	(0.030)	(0.027)
GS Precipitation (100mm)	-0.013	0.015	-0.009	0.000
	(0.027)	(0.018)	(0.017)	(0.017)
Outcome Mean	0.420	0.427	0.427	0.427
Observations	49701	42278	42278	42278
Adjusted$-R^2$	0.085	0.373	0.375	0.375
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
State Birth Year Trends			✓	
Region Birth Year Trends				✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Absolute Upward Mobility in Education and Occupation for individuals aged 15-60 years, using Level based binary indicators, constructed by comparing the educational attainment levels and the occupational groups of children with their fathers respectively (Alesina et al., 2021), weighted using survey weights provided in the survey. The outcomes have been constructed from the Individual Module of IHDS 2011-12 survey. The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into three mutually exclusive categories: White collar, Blue collar, and Agricultural occupations. The white collar category includes professionals, administrative and managerial workers, and clerical workers. Blue collar occupations comprise sales and service workers along with production, transport, and other manual occupations. Agricultural occupations are identified as farm managers, cultivators, agricultural laborers, and workers in fishing and forestry. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, and birth month in all specifications, we progressively account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), followed by state- or region-specific linear trends in birth year. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B7: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Education and Occupation: Regressions with Grid Point Average Weather variables

	(1)	(2)	(3)	(4)
A: Educational Mobility IEM_i				
Grid Point Average GS Temperature (°C)	-0.116***	-0.111***	-0.104***	-0.094***
	(0.031)	(0.025)	(0.024)	(0.024)
Grid Point Average GS Precipitation (100mm)	2.836	1.581	0.240	0.602
	(2.584)	(2.001)	(1.804)	(1.831)
Outcome Mean	0.565	0.564	0.564	0.564
Observations				
Adjusted$-R^2$	0.065	0.232	0.235	0.234
B. Occupational Mobility IOM_i				
Grid Point Average GS Temperature (°C)	-0.078***	-0.051**	-0.043*	-0.047**
	(0.025)	(0.023)	(0.023)	(0.022)
Grid Point Average GS Precipitation (100mm)	2.076	3.183	0.238	1.576
	(2.864)	(2.089)	(1.970)	(1.811)
Outcome Mean	0.417	0.424	0.424	0.424
Observations				
Adjusted$-R^2$	0.086	0.384	0.386	0.386
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
State Birth Year Trends			✓	
Region Birth Year Trends				✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Absolute Upward Mobility in Education and Occupation for individuals aged 15-60 years, using Level based binary indicators, constructed by comparing the educational attainment levels and the occupational groups of children with their fathers respectively (Alesina et al., 2021). The outcomes have been constructed from the Individual Module of IHDS 2011-12 survey. The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into three mutually exclusive categories: White collar, Blue collar, and Agricultural occupations. The white collar category includes professionals, administrative and managerial workers, and clerical workers. Blue collar occupations comprise sales and service workers along with production, transport, and other manual occupations. Agricultural occupations are identified as farm managers, cultivators, agricultural laborers, and workers in fishing and forestry. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons, where we take the average weather variables across all the grid points falling within a district's boundary. Besides fixed effects for district, birth year, and birth month in all specifications, we progressively account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), followed by state- or region-specific linear trends in birth year. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B8: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Education and Occupation: Regressions with Logarithmic Weather variables

	(1)	(2)	(3)	(4)
A: Educational Mobility IEM_i				
Log GS Temperature (°C)	-2.125***	-1.965***	-1.946***	-1.636***
	(0.760)	(0.617)	(0.581)	(0.613)
Log GS Precipitation (100mm)	0.013	0.014	-0.013	-0.006
	(0.032)	(0.027)	(0.026)	(0.026)
Outcome Mean	0.566	0.566	0.566	0.566
Observations	103157	101885	101885	101885
Adjusted$-R^2$	0.064	0.233	0.236	0.235
B. Occupational Mobility IOM_i				
Log GS Temperature (°C)	-1.512***	-1.106**	-1.020**	-1.142**
	(0.561)	(0.461)	(0.503)	(0.451)
Log GS Precipitation (100mm)	0.042	0.050**	0.009	0.022
	(0.037)	(0.024)	(0.023)	(0.023)
Outcome Mean	0.420	0.427	0.427	0.427
Observations	49701	42278	42278	42278
Adjusted$-R^2$	0.089	0.388	0.390	0.389
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
State Birth Year Trends			✓	
Region Birth Year Trends				✓
Non-Growing Season Weather	✓	✓	✓	✓

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Absolute Upward Mobility in Education and Occupation for individuals aged 15-60 years, using Level based binary indicators, constructed by comparing the educational attainment levels and the occupational groups of children with their fathers respectively (Alesina et al., 2021). The outcomes have been constructed from the Individual Module of IHDS 2011-12 survey. The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into three mutually exclusive categories: White collar, Blue collar, and Agricultural occupations. The white collar category includes professionals, administrative and managerial workers, and clerical workers. Blue collar occupations comprise sales and service workers along with production, transport, and other manual occupations. Agricultural occupations are identified as farm managers, cultivators, agricultural laborers, and workers in fishing and forestry. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons, where all these weather variables have been log transformed. Besides fixed effects for district, birth year, and birth month in all specifications, we progressively account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), followed by state- or region-specific linear trends in birth year. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B9: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Education: Specification with Temperature Bins

	Intergenerational Educational Mobility		**Child's Education Rank**	
	(1)	(2)	(3)	(4)
≥ 27(°C)	-0.150***	-0.163***	-4.724**	-5.561**
	(0.056)	(0.056)	(1.877)	(2.223)
25-27(°C)	-0.128***	-0.137***	-3.752**	-3.394*
	(0.046)	(0.048)	(1.483)	(1.912)
23-25(°C)	-0.091**	-0.112***	-2.971***	-3.298**
	(0.041)	(0.042)	(1.102)	(1.301)
21-23(°C)	-0.054***	-0.067***	-0.993	-1.756**
	(0.014)	(0.014)	(0.647)	(0.746)
GS Precipitation (100mm)	0.001	-0.007	0.837	0.451
	(0.015)	(0.016)	(0.826)	(0.813)
District FE	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
State Birth Year Trends	✓		✓	
Region Birth Year Trends		✓		✓
Non-Growing Season Weather	✓	✓	✓	✓
Outcome Mean	0.566	0.566	51.976	51.976
Observations	102090	102090	102090	102090
Adjusted$-R^2$	0.194	0.192	0.360	0.358

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Upward Mobility in Education for individuals aged 15-60 years, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. The first outcome Intergenerational Educational Mobility is a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). The second outcome Child's Education Rank captures the education rank of the individuals, for whom we account for their fathers' education rank (Asher, Novosad, and Rafkin, 2024). The models show the impact across different growing-season temperature bins, relative to the temperature range < 21°C, and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, and birth month, we account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father), along with state- or region-specific linear trends in birth year. Low variability within the Q1 Upper Half mobility variable restricts the binned analysis. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B10: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Education: Regressions using Rainfall Shocks

	Intergenerational Educational Mobility		**Child's Education Rank**		**Bottom Quartile Upper-Half Mobility**	
	(1)	(2)	(3)	(4)	(5)	(6)
GS Temperature (°C)	-0.073***	-0.072***	-2.662**	-2.597**	-0.022*	-0.022*
	(0.024)	(0.023)	(1.221)	(1.213)	(0.013)	(0.013)
Rainfall Shock	-0.002		0.020		0.002	
	(0.004)		(0.187)		(0.002)	
Positive Rainfall Shock		-0.001		-0.119		0.000
		(0.005)		(0.288)		(0.003)
Negative Rainfall Shock		0.001		-0.272		-0.004
		(0.005)		(0.250)		(0.003)
District FE	✓	✓	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
Region Birth Year Trends	✓	✓	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓	✓	✓
Rainfall Shocks	✓		✓		✓	
Wet and Dry Shocks		✓		✓		✓
Outcome Mean	0.566	0.566	51.964	51.964	0.058	0.058
Observations	101885	101885	101885	101885	101885	101885
Adjusted$-R^2$	0.235	0.235	0.378	0.378	0.191	0.191

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Rainfall shocks) on Upward Mobility in Education for individuals aged 15-60 years, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. The first outcome Intergenerational Educational Mobility is a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). The second outcome Child's Education Rank captures the education rank of the individuals, for whom we account for their fathers' education rank (Asher, Novosad, and Rafkin, 2024). The third outcome shows the likelihood of Bottom Quartile Upper-Half Mobility using a binary indicator equal to one if the individual is in the upper half of the education distribution, conditional on fathers in the bottom quartile of their respective education distribution (Corak and Heisz, 1999; Acciari, Polo, and Violante, 2022). The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. We substitute the actual precipitation levels with overall rainfall shocks, and positive (wet) and negative (dry) rainfall shocks (Stainier, Shah, and Barreca, 2026). We control for fixed effects for district, birth year, and birth month, region-specific linear trends in birth year, and standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household) in all the specifications. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B11: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Occupation: Regressions using Rainfall Shocks

	Intergenerational Occupational Mobility		**Mobility towards Non-Agricultural Occupations**		**Human Capital Intensity based Occupational Mobility**	
	(1)	(2)	(3)	(4)	(5)	(6)
GS Temperature (°C)	-0.046**	-0.045**	-0.031*	-0.029*	-0.036*	-0.035*
	(0.018)	(0.019)	(0.016)	(0.017)	(0.020)	(0.021)
Rainfall Shock	0.005		0.001		0.002	
	(0.004)		(0.003)		(0.004)	
Positive Rainfall Shock		0.008		0.005		0.004
		(0.006)		(0.006)		(0.006)
Negative Rainfall Shock		-0.002		0.002		-0.001
		(0.005)		(0.005)		(0.005)
District FE	✓	✓	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
Region Birth Year Trends	✓	✓	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓	✓	✓
Rainfall Shocks	✓		✓		✓	
Wet and Dry Shocks		✓		✓		✓
Outcome Mean	0.427	0.427	0.385	0.385	0.653	0.653
Observations	42278	42278	42278	42278	42278	42278
Adjusted$-R^2$	0.389	0.389	0.493	0.493	0.280	0.280

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Rainfall shocks) on Upward Mobility in Occupation for individuals aged 15-60 years, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. The first outcome Intergenerational Occupational Mobility is a level based binary indicator constructed by comparing the occupational groups of children with their fathers (Alesina et al., 2021). The second outcome shows Mobility towards Non-Agricultural Occupations using a binary outcome equal to one if an individual is engaged in a Non-Agricultural Occupation, and his father is engaged in an Agricultural Occupation. For the third outcome, we follow Brahma (2025) and Ahsan and Chatterjee (2017) and compute human capital score for each occupation as per the National Classification of Occupations (NCO) 1968, and construct a binary indicator for upward mobility, that takes a value equal to one if a child is working in an occupation that has a human capital score higher than that of his/her father. The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into three mutually exclusive categories: White collar, Blue collar, and Agricultural occupations. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. We substitute the actual precipitation levels with overall rainfall shocks, and positive (wet) and negative (dry) rainfall shocks (Stainier, Shah, and Barreca, 2026). We control for fixed effects for district, birth year, and birth month, region-specific linear trends in birth year, and standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household) in all the specifications. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B12: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Education: Quadratic Trends in Birth Year

	Intergenerational Educational Mobility		**Child's Education Rank**		**Bottom Quartile Upper-Half Mobility**	
	(1)	(2)	(3)	(4)	(5)	(6)
GS Temperature (°C)	-0.105***	-0.093***	-3.263***	-3.292***	-0.021*	-0.031**
	(0.025)	(0.025)	(1.146)	(1.238)	(0.012)	(0.013)
GS Precipitation (100mm)	-0.008	-0.010	0.595	0.324	0.002	-0.005
	(0.014)	(0.015)	(0.831)	(0.825)	(0.009)	(0.011)
District FE	✓	✓	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
State Birth Year Trends	✓		✓		✓	
Region Birth Year Trends		✓		✓		✓
Non-Growing Season Weather	✓	✓	✓	✓	✓	✓
Outcome Mean	0.566	0.566	51.965	51.965	0.058	0.058
Observations	101885	101885	101885	101885	101885	101885
Adjusted$-R^2$	0.236	0.235	0.381	0.380	0.196	0.192

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Upward Mobility in Education for individuals aged 15-60 years, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. The first outcome Intergenerational Educational Mobility is a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). The second outcome Child's Education Rank captures the education rank of the individuals, for whom we account for their fathers' education rank (Asher, Novosad, and Rafkin, 2024). The third outcome shows the likelihood of Bottom Quartile Upper-Half Mobility using a binary indicator equal to one if the individual is in the upper half of the education distribution, conditional on fathers in the bottom quartile of their respective education distribution (Corak and Heisz, 1999; Acciari, Polo, and Violante, 2022). The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, and birth month in all specifications, we account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), along with state- or region-specific quadratic trends in birth year, in lieu of linear trends in our baseline specifications. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B13: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Occupation: Quadratic Trends in Birth Year

	Intergenerational Occupational Mobility		**Mobility towards Non-Agricultural Occupations**		**Human Capital Intensity based Occupational Mobility**	
	(1)	(2)	(3)	(4)	(5)	(6)
GS Temperature (°C)	-0.105***	-0.093***	-0.035*	-0.040**	-0.041*	-0.048**
	(0.025)	(0.025)	(0.019)	(0.018)	(0.023)	(0.021)
GS Precipitation (100mm)	-0.008	-0.010	-0.014	-0.010	-0.006	-0.003
	(0.014)	(0.015)	(0.012)	(0.012)	(0.014)	(0.013)
District FE	✓	✓	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
State Birth Year Trends	✓		✓		✓	
Region Birth Year Trends		✓		✓		✓
Non-Growing Season Weather	✓	✓	✓	✓	✓	✓
Outcome Mean	0.566	0.566	0.385	0.385	0.653	0.653
Observations	101885	101885	42278	42278	42278	42278
Adjusted$-R^2$	0.236	0.235	0.493	0.493	0.280	0.280

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Upward Mobility in Occupation for individuals aged 15-60 years, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. The first outcome Intergenerational Occupational Mobility is a level based binary indicator constructed by comparing the occupational groups of children with their fathers (Alesina et al., 2021). The second outcome shows Mobility towards Non-Agricultural Occupations using a binary outcome equal to one if an individual is engaged in a Non-Agricultural Occupation, and his father is engaged in an Agricultural Occupation. For the third outcome, we follow Brahma (2025) and Ahsan and Chatterjee (2017) and compute human capital score for each occupation as per the National Classification of Occupations (NCO) 1968, and construct a binary indicator for upward mobility, that takes a value equal to one if a child is working in an occupation that has a human capital score higher than that of his/her father. The survey provides detailed primary occupation codes for individuals. Following Hnatkovska, Lahiri, and Paul (2012), we collapse them into three mutually exclusive categories: White collar, Blue collar, and Agricultural occupations. We exclude respondents with missing or unidentifiable occupation codes, and those reported to be out of the labor force. The models show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for district, birth year, and birth month in all specifications, we account for standard demographics (gender, age, age squared, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), along with state- or region-specific quadratic trends in birth year, in lieu of linear trends in our baseline specifications. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B14: Impact of In-Utero Exposure to Growing Season Temperature on Upward Mobility in Education: Mediation by Major Health Morbidity using Instrumental Variable Specification

	Intergenerational Educational Mobility	**Child's Education Rank**	**Bottom Quartile Upper-Half Mobility**
	(1)	(2)	(3)
Major Health $\widehat{\text{Morbidity}}$ Score	-1.496**	-79.546**	-0.787**
	(0.605)	(31.394)	(0.312)
GS Precipitation (100mm)	-0.024	-0.496	-0.014
	(0.028)	(1.406)	(0.017)
District FE	✓	✓	✓
Birth Year FE	✓	✓	✓
Birth Month FE	✓	✓	✓
Demographic Controls	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓
Outcome Mean	0.566	51.965	0.058
Observations	101885	101885	101885
Uncentered$-R^2$	0.204	0.652	-1.043
First Stage F-Statistic	11.45	11.14	11.45

Notes: Table reports the impact of In-utero Exposure to preceding decade's Growing Season (GS) Temperature (and Precipitation) on Upward Mobility in Education for individuals aged 15-60 years, mediated by Major Health Morbidity, using outcomes constructed from the Individual Module of IHDS 2011-12 survey. The first outcome Intergenerational Educational Mobility is a level based binary indicator constructed by comparing the educational attainment levels of children with their fathers (Alesina et al., 2021). The second outcome Child's Education Rank captures the education rank of the individuals, for whom we account for their fathers' education rank (Asher, Novosad, and Rafkin, 2024). The third outcome shows the likelihood of Bottom Quartile Upper-Half Mobility using a binary indicator equal to one if the individual is in the upper half of the education distribution, conditional on fathers in the bottom quartile of their respective education distribution (Corak and Heisz, 1999; Acciari, Polo, and Violante, 2022). *Major Health Morbidity* captures the mediation impact, which we instrument using in-utero exposure to temperature (°Celsius) for the growing season. Regressions control for in-utero exposure to precipitation (100 mm) for the growing season, and weather variables in the non-growing season, while accounting for standard demographics (gender, age, and marital status of individual, and fixed effects for educational and occupational levels of father, and caste and religion of the household), and fixed effects for district, birth year, and birth month. *Major Health Morbidity* is a score (ranging from 0 to 2) assigned to an individual having a major morbidity (among fourteen major problems including high blood pressure, heart disease, diabetes, cancer, asthma, and others). The First Stage F-Statistic shown in the table is the Kleibergen-Paap Wald F-Statistic computed for the Weak Identification Test. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B15: Impact of Exposure to Growing Season Temperature on Major Morbidity Outcomes: Validation for Contemporaneous Health Effects

	(1) **MSI Index (using z-scores)**	(2) **MSI Index (using PCA)**	(3) **High Blood Pressure**	(4) **Heart Disease**	(5) **Diabetes**	(6) **Obesity**
GS Temperature (°C)	2.363***	4.198***	0.331**	0.112***	0.398***	0.317*
	(0.674)	(1.566)	(0.167)	(0.040)	(0.114)	(0.173)
GS Precipitation (100mm)	-1.822*	-4.043*	-0.232	-0.247***	0.009	-0.589**
	(1.032)	(2.242)	(0.247)	(0.070)	(0.165)	(0.254)
Outcome Mean	-0.002	-0.001	0.022	0.006	0.012	0.028
Observations	182658	122400	182658	182658	182658	122400
Adjusted$-R^2$	0.102	0.120	0.070	0.016	0.059	0.046
	(7) **Any Major Morbidity**	(8) **Overweight**	(9) **Underweight**	(10) **Tuberculosis**	(11) **Asthma**	(12) **Days disabled last year**
GS Temperature (°C)	0.859***	0.781***	0.534	0.084***	0.105**	49.728***
	(0.248)	(0.286)	(0.351)	(0.027)	(0.041)	(14.105)
GS Precipitation (100mm)	-0.484	-0.345	0.558	-0.046	-0.095*	-46.946***
	(0.344)	(0.377)	(0.456)	(0.029)	(0.055)	(17.700)
Outcome Mean	0.080	0.104	0.449	0.003	0.006	2.905
Observations	182658	122400	122400	182658	182658	182658
Adjusted$-R^2$	0.116	0.124	0.417	0.008	0.013	0.022
Region FE	✓	✓	✓	✓	✓	✓
Birth Year FE	✓	✓	✓	✓	✓	✓
Birth Month FE	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Region × Birth Year FE	✓	✓	✓	✓	✓	✓
District - Birth Year Trends	✓	✓	✓	✓	✓	✓
Non-Growing Season Weather	✓	✓	✓	✓	✓	✓

Notes: Table reports the impact of Exposure to preceding decade's Growing Season (GS) Temperature (and Rainfall Shocks) on long-run Health outcomes of individuals, constructed from the Household Module of IHDS 2011-12 survey. Models 1 and 2 show Metabolic Syndrome Index, constructed by averaging standardized z-scores of high blood pressure, heart disease, diabetes, and obesity (Hoynes, Schanzenbach, and Almond, 2016), and applying Principal Component Analysis respectively. Models 3 to 6 show the indicators for the four components as binary variables: the first three showing whether the individual has high blood pressure, heart disease and diabetes respectively. The fourth component, Obesity, is a binary indicator equal to one if the body mass index is greater than or equal to 30 kg/m^2 (Sekhri and Shastry, 2024; Singh et al., 2025). Model 7 shows any major morbidity the individual has currently. Models 8 and 9 show the probability of an individual being overweight and underweight respectively. Models 10 and 11 show binary indicators for an individual having Tuberculosis and Asthma respectively. Model 12 shows the number of days an individual was disabled in the last one year. The regressions show the impact of growing-season temperature (°Celsius) and rainfall (100 mm), controlling for the weather in the non-growing seasons. Besides fixed effects for region zones (Central, East, North, South, North-East, and West), individual's birth year, birth month, region × birth year, and district specific linear trends in birth year, all specifications account for the gender of the individual, age, quadratic in age, marital status, along with household characteristics, including, total household assets owned, binary indicators for ownership of land, ownership of nonfarm business, outstanding debt in the last five years, BPL card ownership, urban residence, poverty status, and fixed effects for caste, religion, and main source of income. Robust standard errors clustered at the district level are reported in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$