The Long-Term Human Capital Consequences of Exposures to Natural Disasters: Evidence from India

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Abstract

Natural disasters driven by accelerating climate change have significant implications for human capital. This paper investigates the long-term effects of early-life exposures to natural disasters on human capital formation, focusing on educational attainment, health outcomes, and labor force participation during adolescence and early adulthood. By linking over 500 natural disasters in India recorded in the EM-DAT database with panel data from the India Human Development Survey (IHDS) at the district and year level, I construct a sample of 71,000 individuals aged 14 to 40 at the time of the second-wave interview (2011-2013), with natural disaster exposure trajectories in early life. Exploiting geographical and temporal variations in the exposures, the study identifies significant adverse effects of early-life disaster exposures on human capital. The results indicate that early-life exposures to natural disasters leads to lower educational attainment, higher prevalence of chronic health conditions, and reduces labor force participation in general and monthly or annually paid employment. Analysis of yearly exposure histories reveals that natural disasters occurring during the birth year and the subsequent year significantly reduce the probability of receiving education, while health is more adversely affected by exposures during the in-utero and birth year periods. Both genders experience negative impacts on labor force participation, with more pronounced effects for women, particularly in terms of participation in formal, wage-based employment.

Keywords: Natural disasters, human capital, education, health, labor market outcomes

JEL: E24, I14, I24, Q54

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1 Introduction

Between 1970 and 2019, the United Nations reported a significant increase in natural disasters due to climate change and extreme-weather events (United Nations 2021). Not only has the number of recorded natural disasters risen markedly (Van Aalst 2006; Helmer and Hilhorst 2006), but the intensity of these events has also escalated, driven by climate change (Coronese et al. 2019; Berz et al. 2001). Natural hazards accounted for 50 percent of all disasters, 45 percent of all reported deaths and 74 percent of all reported economic losses (United Nations 2021). In the coming decades, climate change is expected to further increase the frequency and severity of natural disasters such as floods, droughts, and extreme weather events (Intergovernmental Panel on Climate Change 2022). Typically, the severity of natural disasters escalates with greater power and intensity, although this is not always the case. Unpredictable natural disasters, such as sudden earthquakes or flash floods, create immediate disruptions with minimal warning, leaving little time for preparation. But regions more frequently impacted by certain types of disasters may become better prepared or adapted to such events, potentially mitigating severity (Caldera and Wirasinghe 2022). Capturing the real shocks for locations during certain time hence becomes one important question.

Short-term interruptions can lead to long-term effects of disaster exposure on human capital development and accumulation. Adverse conditions in early life may have enduring impacts. A growing body of literature documents the lasting effects of early childhood shocks on child development (Currie 2009) and on adulthood outcomes such as education, health, and socioeconomic status (Alderman, Hoddinott, and Kinsey 2006; Almond 2006; Rosales-Rueda 2018; Maluccio et al. 2009). However, there is fewer research on the impact of natural disaster exposure during critical developmental periods and its effects on education, health, and labor outcomes in adulthood.

This paper addresses the following research questions: What are the long-term effects of exposure history to natural disasters on human capital during adolescence and early adulthood? Does the timing or age at which exposure occurs influence the magnitude and direction of these effects? Additionally, do the disruptive impacts of early exposure to natural disasters manifest in later life? To estimate these impacts, I use data on all natural disasters occurring in India since 1970, combined with the panel sample from Indian Human Development Survey (IHDS). Given the potential serial correlation of natural disasters over time, events experienced in the years surrounding the birth year may influence adult outcomes, extending beyond the in utero period. Therefore, it is crucial to examine whether the timing of exposure is significant for the observed outcomes.

Using the panel sample from Indian Human Development Survey (IHDS), I conduct individuals' exposure to natural disasters from conception to the age 2. Natural disaster shocks can cause changes in prenatal stress (Andrabi, Daniels, and Das 2021; Charil et al. 2010; Fuller 2014), and central nervous system and brain grow rapidly between 8 and 25 weeks post-conception, which is essential for cognitive development (Almond, Edlund, and Palme 2009). Preliminary findings indicate a significant negative effect of disaster exposure on the probability of receiving any level of education, a positive effect on chronic illness expenses, and a negative effect on labor force participation, regardless of wage employment.

My findings contribute to economic research in several dimensions. First, while most studies investigating the long-term effects of natural disaster exposure on human capital focus on single events (Cho and Kim 2023; Ciraudo 2020), fewer studies examine a broad spectrum of natural disasters (Opper, Park, and Husted 2023; Currie and Vogl 2013; Norling 2022) and consider the intensity of natural disaster events (Caruso 2017). Considering multiple disaster shocks and their intensity is crucial, especially in disaster-prone areas where natural disasters are correlated.

Second, this paper explores the long-term human capital effects from trajectories of natural disaster exposure. Some studies suggest early-life impacts can fade over time (Currie and Almond 2011; Almond, Currie, and Duque 2018), while others argue that childhood harms can increase proportionally as individuals age due to the cumulative nature of human capital production (Hanushek and Rivkin 2012; Todd and Wolpin 2003). Previous research has shown that negative impacts during critical periods of fetal and infant development reduce human capital in later life, leading to lower labor productivity, income, and poorer health (Almond 2006; Karbownik and Wray 2019; Maccini and Yang 2009; Shah and Steinberg 2017). This paper adds evidence to this literature by focusing on the effects of extreme natural disaster events.

The rest of this paper is organized as follows. Section 2 describes data and construction of key measures. Section 3 presents summary statistics. Section 4 describes the estimation strategy. Section 5 presents and interprets the main results. Section 6 concludes.

2 Data

2.1 Data on Human Capital

I use the India Human Development Survey (IHDS) (Desai, Vanneman, and National Council of Applied Economic Research 2019) to examine the long-term consequences of natural disaster exposures on human capital formation. The IHDS is a nationally representative, multi-topic panel survey conducted in two waves—carried out in 2004-2005 and 2011-2012—encompassing over 41,000 households.[1] Each wave includes two one-hour interviews per household, with precise geographical data recorded at the district level (administrative level 2). The survey's extensive temporal coverage and broad geographical scope provide an invaluable opportunity to explore the evolving daily lives of Indian households amid rapid societal transitions and environmental changes (Azam and Bhatt 2015; Chatterjee and Sennott 2021; Heyes and Saberian 2022; Mohanty and Gebremedhin 2018).

Sample. The second wave (IHDS-II) re-interviewed about 83% of the households from the first wave (IHDS-I), including any split households that resided within the same community. In IHDS-I, 215,751 individuals were surveyed, of which 64,763 were only interviewed in IHDS-I. IHDS-II surveyed 204,560 individuals, including 53,577 who were only interviewed in the second wave. Consequently, the full IHDS panel comprises 150,983 individuals. My analysis focuses on a subset of this panel, specifically individuals who were aged 14 to 40 years at the time of interview in the second wave (IHDS-II). This results in a sample of 71,922 individuals for whom early-life exposures to natural disasters, beginning in 1970, are constructed.

Migration. I assume that individuals in the panel sample did not move across districts since conception, based on several pieace of information.

First, for every observation in full panel sample, the district of residence in IHDS-I (surveyed in 2004-2005) and IHDS-II (surveyed in 2011-2013) are recorded, and all of them report the same district of residence in both waves. While this does not preclude the possibility of migration during the intervening years, one may assume that these individuals did not move across districts during this period. Second, IHDS-II asks individuals about migration history in recent 5 years related to seasonal or short-term work. Out of 150,983 individuals, 98.13%

1. A third wave is currently in the field.

have not migrated.[2] Third, both IHDS-I and IHDS-II ask about migration history at household level. 77.88% households have been living for more than 90 years in the same village/twon/city, which are geo-locations at a finer level than district, and 37,883 out of 42,152 households (90%) have not moved across districts.[3]

I further construct human capital outcomes based on information collected during the second wave, capturing more recent and longer-term measures of human capital development, as detailed in Section 2.3.1.

2.2 Data on Natural Disasters

The natural-disaster variables are derived from the EM-DAT database (1900-2023) (Delforge et al. 2023). EM-DAT, compiled by the Centre for Research on the Epidemiology of Disaster (CRED), offers comprehensive information on natural disasters that have led to significant human losses and are classified as geophysical, meteorological, hydrological, climatological, or biological (Mavhura and Raj Aryal 2023). It is compiled from a variety of sources, including United Nations agencies, non-governmental organisations, insurance companies, research institutes, and press agencies. Disasters are included in the EM-DAT database if they meet at least one of the following criteria: (a) ten or more people killed, (b) one hundred or more people affected, (c) the declaration of a state of emergency, or (d) a call for international assistance (Panwar and Sen 2020; Mavhura and Raj Aryal 2023; Sy et al. 2019).

EM-DAT is the most widely employed resource for studying the impacts of disaster shocks on long-term, multi-dimensional economic outcomes such as GDP growth (Botzen, Deschenes, and Sanders 2019; Klomp and Valckx 2014). A meta-analysis of macroeconomic literature concludes that over 60% of 64 primary studies published in 2000–2013 used EM-DAT (Lazzaroni and Bergeijk 2014). For example, it has been used to estimate average outcomes in 73 nations (Kahn 2005), 89 countries (Skidmore and Toya 2002), 108 countries (Felbermayr and Gröschl 2014), and for 109 countries (Noy 2009) over several decades. The effects of disasters on firm-level outcomes, including employment, asset accumulation, and productivity, have also been

2. The survey question is "have you or any member of your household left to find seasonal/short term work during last five years and returned to live here". 2,827 out of 150,983 individuals are recorded as "yes". Then, the place of migration is recorded in these categories: "same state"—1,350 (0.9%) individuals, "another state"—1,406 (0.9%) individuals, "abroad"—71 individuals.

3. The survey question is "how many years ago did your family first come to this village/town/city". 32,829 out of 42,152 households included in IHDS-II are recorded as "live here since forever". For those who have lived in the current place, the place of origin is recorded in these categories: "same state, same district"—5,054 (12%) households, "same state, another district"—2,122 (5%) households, "another state"—1,396 (3%) households, "another country"—646 (1.5%) households.

examined using panel data of European firms and EM-DAT (Leiter, Oberhofer, and Raschky 2009). Thanks to the detailed recording of various types of disasters in EM-DAT, researchers can aggregate different disasters occurring in certain locations and time spans into a single index (Botzen, Deschenes, and Sanders 2019). For example, measures of disaster severity considering fatality counts above certain thresholds, have been constructed from EM-DAT (or ARC records) for a county-level study in the U.S. (Boustan et al. 2020). Caruso 2017 examines the long-term effects and intergenerational transmission of exposure to natural disasters in childhood using EM-DAT records for Latin America in the past century.

2.3 Measures

2.3.1 Human Capital Variables

Educational outcomes. The measure of whether an individual has ever received education is derived from a question asking if the individual has ever attended school. In addition to this, the analysis includes variables such as years of education, an indicator of whether the individual has completed lower primary school, and an indicator of whether they have completed upper primary school.

Short-term sickness. In the Income and Social Capital module of the IHDS, respondents are asked about the health of various household members, including very young children, over the past 30 days. The survey specifically considers three illnesses—fever, cough, and diarrhea—to assess short-term sickness. I construct an indicator variable to denote whether an individual has experienced any of these illnesses in the last 30 days, as well as a continuous variable representing the number of days the person was sick.

If an individual received any treatment or advice, or was hospitalized, the survey records the total cost of treatment, including surgery, medicines, and both outpatient and inpatient services. Additionally, the costs for medicines, tests, tips, and transportation are recorded separately. These are combined to calculate the total health expenditure for short-term sickness, which is then logarithmically transformed. The original values are in rupees, with a value of zero assigned if no money was spent.

Long-term disease. Beyond the past 30 days, the IHDS also inquires whether a doctor has ever diagnosed any household member with a chronic disease such as cataracts, tuberculosis (TB), high blood pressure, heart disease, and similar conditions. An indicator variable for long-term disease is constructed, coded as 1 if an individual has had or been cured of any of these diseases, and 0 if not diagnosed with such conditions. An indicator for long-term disease is constructed, coded as 1 if an individual has had or been cured of any of these diseases, and 0 if not diagnosed with such diseases.

Similarly, health expenditure for long-term diseases—including costs for doctors, medicines, hospital stays, and transportation—is calculated and logarithmically transformed for analysis.

Labor force participation for any type of work. The IHDS collects labor-related data through an extensive set of income questions. The survey inquires if an individual is working on a farm, in a business, or earning a salary/wage, collecting such information for men, women, and children to capture a comprehensive picture of economic activities involved by all individuals in the households in the preceding year. This allows us to observe whether an individual has participated in any type of work.

Labor force participation with salary paid monthly or annually. Workers are categorized into three types: salaried workers who are paid monthly or annually, agricultural workers who are paid daily and report an agricultural occupation, and all other daily wage workers recorded as non-agricultural workers. A dummy variable is used to indicate if an individual is a salaried worker paid monthly or annually, serving as a proxy for more stable employment status or longer-term contracts, which may correlate with higher ability and better physical health.

2.3.2 Exposures to Disasters

Type A: Any disasters in EM-DAT. Using location names affected by each disaster recorded in EM-DAT data, I link disasters to district in India. The location names can be state or district, and if it is state recorded, it means the entire state has been affected by that event. I use 2001 Indian division to link the states with districts. Then, by using the starting and ending dates of each disaster, along with the interview dates and ages of individuals in the survey data, disasters are matched to each year and district. I construct a binary indicator of disaster exposure for each individual in each year, denoted as $DI_{il,t}$. This indicator equals one if location l in year t has experienced any disasters and zero otherwise. For person i residing in location l, this variable is assigned accordingly. For certain period j which is longer than one year, I construct binary indicator for the existence of natural disasters denoted as $Disaster_{il,j}$. This means the natural disaster experience indicator in early life which is defined as the time from conception to age 2 is constructed by

$$Disaster_{il,earlylife} = \mathbf{1}\{\sum_{t \in earlylife} DI_{il,t} \geq 0\} \tag{2.1}$$

Type S: District-level standardized disaster shocks. To gauge the magnitude of shocks experienced by a district within a year, I analyze the deviation in the number of disasters occurring annually in each district. For each district l in year t, I calculate the number of disasters $DisN_{lt}$ and determine the mean and standard deviation of the number of disasters experienced by district l from 1970 to 2014. If, in any given year, the number of disasters experienced by a district exceeds this mean by two standard deviations, the corresponding district year is labeled as "experiencing disaster shock" ($DisShock_{lt} = 1$). For individual i, the disaster exposure indicator $Disaster_{il,j} = 1$ if there was one disaster shock district-year during period j:

$$\begin{aligned} DisShock_{lt} &= \mathbf{1}\{DisN_{lt} > Mean(DisN_{l,1970-2014}) + 2 \times SD((DisN_{l,1970-2014})\} \\ Disaster_{il,j} &= \mathbf{1}\{\sum_{t \in j} DisShock_{lt} > 0\} \end{aligned} \tag{2.2}$$

3 Summary Statistics

3.1 Natural Disasters in India

The EM-DAT database records natural disasters as individual events. Figure 1 shows the number of natural disaster events per year and presents the trends for all types of events, as well as for floods and storms separately. Between 1970 and 2014, a total of 534 natural disaster events were recorded in India, with no single year being "disaster-free". The year 2005 stands out as the most "disastrous" year, with a significant peak exceeding 30 events. The overall frequency of natural disasters, particularly floods and storms, has increased over the decades. Most natural disasters occurred and concluded within the same calendar year.[4]

4. This does not mean they last more than 12 months, but the start year and end year are different. These include events with identification number "1972-9116-IND, 1982-9350-IND, 2000-9222-IND, 2003-0636-IND, 2005-0701-IND, 2005-0754-IND, 2007-0674-IND, 2008-0616-IND, 2012-0538-IND, 2015-9618-IND, 2018-9372-IND". All of them ended in the next year.

3.1.1 Disaster Characteristics

In Table 1, the natural disaster events are categorized by type of events and summarized with more detailed information on their consequences, including the number of deaths, the number of people affected, and the economic damage incurred in terms of US dollars (1,000 unit). The intensity, unpredictability, and consequences of these disaster types vary, and there is potential for serial correlation among them. The climate of India is predominantly shaped by the summer monsoon, which spans from June to September. The year can be typically divided into four distinct seasons: (1) January and February, (2) March to May, (3) June to September, and (4) October to December. Each season is associated with a range of extreme weather events, such as storms, heat waves, tropical cyclones, tidal waves, floods, landslides, and droughts (De, Dube, and Rao 2005).

Among the 534 recorded events, floods (222 occurrences) and storms (113 occurrences) are the most prevalent, together accounting for more than half of all natural disasters in India. On average, India experiences 5 floods annually, with each flood resulting in approximately 260 deaths and affecting around 4 million people. Floods have a significant human impact compared to most other disasters, second only to droughts in terms of the number of people affected. Storms are the second most frequent phenomenon, with 113 events occurring between 1970 and 2014, and they can be highly related to floods. Inland flooding usually occurs during or after a heavy, slow-moving rain storm as well as strong coastal storms (Mall, Kumar, and Bhatla 2011; Bhaskaran, Rao, and Murty 2020). On average, almost more than 2 storms are expected per year. This type of event can be more destructive than floods in terms of casualties, as the number of people killed by storms is the second only to earthquakes, with more than 400 deaths per event. The economic damages are also substantial, as high as droughts and earthquakes often exceeding $1 billion USD. There were 62 epidemics in India from 1970 to 2014. Most of these were caused by viral (31 events), bacterial (20 events), or parasitic (5 events) diseases. Taking a closer look at the event names, cholera is found to be the most frequent disaster (12 events), which is still considered as an under-recognized health problem in India even though it has existed for centuries (Ali et al. 2017; Mogasale, Mogasale, and Hsiao 2020).[5] Extreme temperature events, including cold waves (28 events), heat waves (20 events), and severe winter

5. There are 6 events not categorized into any subtypes. For "EventName", there is one acute diarrhoeal syndrome, one is acute neurological syndrome, one enteric disease, one gastroenteritis, and two events do not have that. Second common disaster to cholera is Japanese encephalitis with 9 events.

conditions (2 events), were recorded 50 times from 1970 to 2014. This type of disasters may be associated with other disaster events, such as drought may follow heat wave; but in EM-DAT, it does not show this pattern. EM-DAT records the secondary disaster types cascading from or co-occurring aside from the main type, but in all extreme temperature events, only few (6 events) are reported with associated disasters, such as snow/ice, fog, and drought.

3.1.2 Distribution of District-level Disaster Exposures

Figure 2 illustrates the geographical variation in the number of natural disasters across each district in India as recorded in EM-DAT. This corresponds to the Type A exposure measures described in Section 2.3.2. To capture temporal trends, the data is segmented into 10-year windows and each sub-figure presents one window. States within the "India Flood Prone Areas"—including West Bengal, Orissa, Andhra Pradesh, Kerala, Bihar, Gujarat, Uttar Pradesh, Haryana, and Punjab—are identified as "disaster-prone areas." Uttar Pradesh experienced the highest number of events from 2001 to 2010, with over 35 events.

While Figure 2 presents the type A disaster exposure measure, Figure 3 displays the geographical distribution of the type S disaster exposure measure (only 2001-2010 period is shown in this map). The type S measure, which captures the number of years in shock for each district, shows that the northern disaster-prone areas identified in Figure 2 are not as prominently "shock-prone" under this measure.

3.2 Human Capital Outcomes

3.2.1 Sample Overview

An overview of the sample composition and human capital variables is presented in Table 2. The total sample comprises 71,922 individuals, with 45% of them being female. The average age is 26 years, and the survey was conducted across 2011, 2012, and 2013. For caste and religion, historically marginalized Hindu castes—Other Backward Castes (OBC), Scheduled Castes (SC), and Scheduled Tribes (ST) or Indigenous groups—are grouped into a category termed "Hindu marginalized caste". This contracts with the historically privileged Hindu Upper Castes ("Hindu upper caste" in the table) and the third group, "Muslim". In the sample, more than 99% of individuals reveal their caste and religion information, among whom 20% are identified as "Hindu upper caste" while 64% belong to the Hindu marginalized caste. Regarding educational attainment, 84% of individuals have received some education. Additionally, 6% have experienced a chronic disease at some point in their life, regardless of recovery status. More than 60% of the sample participates in some type of work, with only 12% of the entire sample working for a monthly or annual salary.

3.2.2 Human Capital and Disaster Exposures

Table 3 presents summary statistics of human capital outcomes and disaster exposure history across genders. The top panel shows the distributions by considering Type A disaster exposure measures, while the bottom panel presents that of Type S. In each panel, the first part shows the distribution of exposures to disasters separately for males and females. Then, in the second part, the sample is divided into four groups: males exposed to natural disasters in early life, males not exposed to natural disasters in early life, females exposed to natural disasters in early life, and females not exposed to natural disasters in early life. For each group, it displays the proportion of individuals who have ever been educated, the proportion who have ever had long-term disease, the labor force participation rate for any type of employment, and the rate for salary workers paid monthly or annually.

The sample consists of 39,429 males, of whom 28,418 (72.1%) were exposed to natural disasters in early life if any disasters recorded in EM-DAT are counted. Among 32,493 females, 22,583 (69.6%) were similarly exposed. However, when considering district-level standardized disaster shocks, the proportion of individuals exposed to disasters decreases significantly for both genders across all early life stages. Specifically, 4.3% of males and 4.4% of females experienced Type S disaster shocks in early life, with an average exposure rate of about 1% in each critical period, including in utero, from birth to age 1, and age 1 to 2.

The proportion of males who have received education is higher than that of females. When considering Type A disaster exposure measures, the difference in educational attainment between those exposed and unexposed to natural disasters in early life is approximately 2.6 percentage points for males, compared to a significantly larger difference of 9.3 percentage points for females. This pattern is also observed with Type S disaster exposure measures, where the difference is 6 percentage points for males and 18 percentage points for females. Females generally exhibit a higher prevalence of long-term diseases. It is noticeable that within each gender, individuals exposed to disasters in early life tend to have higher educational attainment and a lower incidence of long-term disease. This may be attributable to survivor bias, suggesting that those who survived disasters are healthier and have more resources to cope with disaster shocks. Overall, females have lower labor force participation rates compared to males. These differences likely stem not from disaster exposure in early life but from disparities in educational attainment, health status, and traditional norms that restrict female labor force participation. Nevertheless, it is noteworthy that among females, those exposed to disasters exhibit significantly lower labor force participation rates, regardless of the type of disaster exposure or type of work.

I furthermore provide illustrative evidence on disaster exposures and human capital outcomes using the trends of outcomes over ages. Figures 4a, 4b, 5a, and 5b illustrate the trends over age for four different outcome variables, categorized by gender and early-life exposure to natural disasters. These trends are presented unconditionally, without accounting for any additional factors.

In Figure 4a, the proportion of individuals who have ever been educated is shown over age. Males who did not experience early-life shocks exhibit the highest overall ratio of education attainment. Within each gender, those exposed to natural disaster shocks in early life have a lower education attainment ratio compared to their non-exposed counterparts. Figure 4b depicts the likelihood of having been diagnosed with chronic diseases, which naturally increases with age. Notably, females exposed to early-life shocks exhibit the highest probability of having chronic diseases. For individuals over age 35 who experienced early-life natural disaster shocks, the proportion of having had chronic diseases exceeds 12.5%. In Figure 5a, labor force participation rates are examined. It is not surprising that females generally have lower labor force participation rates compared to males across all ages as it is well documented in the literature about India labor market. However, the difference between males with and without early-life shocks is much less pronounced than that for females. The two lines for males with and without early-life shocks almost overlap, potentailly suggesting minimal differences in labor force participation for this group. Figure 5b focuses on labor force participation specifically for jobs with monthly or annual salaries. As a result, the ratio is considerably lower compared to Figure 5a. Although there are gaps in labor force participation of this type of jobs between those exposed to shocks and those not exposed, the differences are relatively modest for both females and males.

4 Estimation Strategy

To estimate ths effects of early-life exposures to natural disasters on educational and health outcome, and labor force participation, I employ the following reduced-form regression leveraging jointly temporal and spatial variations in disaster exposures across geographic identifiers and interview timings:

$$Y_{ilty} = \alpha + \beta \cdot Disaster_{il,earlylife} + \mu_l + \phi_{g_i(t)} + \psi_y + \gamma X_{i,y} + \epsilon_{ilty}, \tag{4.1}$$

where Y_{ilty} represents the human capital measures for individual i residing in district l, born in year t, and surveyed in year y. $Disaster_{il,earlylife}$ is the indicator of natural disaster exposure of i during early life, using either Type A or Type S disaster shock measures. The model includes a vector of district fixed effects μ_l to account for unobserved heterogeneity at the district level, which are at the same (or lower) level of geographical aggregation as the disaster variables. Individual-age fixed effects $\phi_{g_i(t)}$ are also incorporated, where $g_i(t)$ denotes the age-specific mapping function that links interview year t and age g. Additionally, it includes survey year and month fixed effects ψ_y[6] The vector $X_{i,y}$ includes individual-level control variables such as gender, caste, and religion. The error term ϵ_{ilty} is assumed to be random and idiosyncratic, with standard errors clustered at the district level.

This identification strategy exploits exogenous variation in geographic location, interview timing, and cohort-specific exposures to natural disasters. Through district fixed effects, it accounts for within-district variations in disaster experiences due to differences in survey timing and age-related heterogeneities. The inclusion of interview timing fixed effects further mitigates potential biases arising from correlations between disaster exposure and seasonal patterns, as well as secular trends in health outcomes and decisions regarding education and labor force participation.

I furthermore estimate the following equation to examine the trajectory of natural disaster exposure by age during critical developmental periods:

$$Y_{ilty} = \alpha + \sum_{j \in TimeSpan} \beta_j \cdot Disaster_{il,j} + \mu_l + \phi_{g_i(t)} + \psi_y + \gamma X_{i,y} + \epsilon_{ilty}, \tag{4.2}$$

where Y_{ilty} still represents the human capital measures for individual i in district l, born in year

6. For simplicity, the survey month subscript is suppressed.

t, and surveyed in year y. $Disaster_{il,j}$ represents the natural disaster exposures of individual i in year j. The $TimeSpan$ includes the periods $\{inUtero, age1, age2\}$; the coefficients β_j capture the yearly age-specific impacts of disaster exposure during early life on long-term outcomes. By estimating this model, I implicitly assume that the differing effects of disaster exposures in each year during the critical development period on the outcomes of interest are homogeneous as they age. This specification allows for a comparison between individuals from the same district but born in different cohorts. Since the regression contains district-level fixed effects, the estimated coefficients are not biased by systematic differences across districts. This approach provides a more nuanced understanding of how the timing of disaster exposure influences long-term human capital formation.

5 Results

5.1 Educational and Health Outcomes and Disaster Exposures

Aggregate early-life exposures. Equation 4.1 is estimated using a linear probability model, with the results presented in Table 4, Table 6, Table 5, and Table 7. The regression analysis explores the impacts of early-life exposure to natural disasters on various educational and health outcomes: the likelihood of receiving any education, years of education completed, the likelihood of completing lower primary school, and the likelihood of completing upper primary school; as well as the incidence of long-term disease and short-term sickness, with corresponding health expenditures. The regressions in all columns control for gender, caste and religion, while incorporating district fixed effects, interview year and month fixed effects, and age fixed effects to control variations across cohorts within districts.

When considering all disasters recorded in EM-DAT (Table 4), individuals aged 14 to 40 who experienced natural disasters during early life show, on average, a 1.4 percentage point reduction in the probability of having received any education. Additionally, females are found to be 12.6 percentage points less likely to have received an education compared to males. In terms of health outcomes, the probability of having or having had a long-term disease is marginally higher for those who experienced Type A disaster exposures early in life. Females, in particular, are adversely affected, facing a 3.2 percentage point higher probability of having a long-term disease compared to males. Table 5 supports these findings, indicating that early-life disaster exposure is positively associated with the occurrence of long-term diseases.

Trajectory of early-life exposures. The impact of early-life exposure to natural disasters at various developmental stages on adult outcomes is subsequently estimated. The findings in Table 4 and Table 5 demonstrate that early-life experiences significantly influence adult outcomes. Nevertheless, the results do not pinpoint in utero or infancy exposure to natural disasters as critical factors in shaping adult human capital outcomes. Given the potential serial correlation of natural disasters over time, it is plausible that events occurring post-utero have substantial impacts on adult outcomes. This raises the possibility that the coefficients for early-life exposure to natural disasters may be capturing the effects of infancy exposure rather than solely in utero exposure. To address this, Equation 4.2 is estimated, with results detailed in Table 6 and Table 7. The estimated coefficients are presented with gender omitted for brevity.

Shown in Table 6, exposures between the ages of 1 and 2 appears to be positively associated with the likelihood of receiving education and the number of years of education completed. Conversely, exposure during the birth year is negatively associated with the incidence of short-term sickness. These patterns may be influenced by selection and survivor bias, or by the level of preparedness and adaptation to natural disasters in certain regions. In comparison, Table 7 reveals that in utero exposure to disasters increases the likelihood of having experienced a long-term disease by 1.9 percentage points, with a similar effect observed for exposure during the birth year (1.8 percentage points). This analysis indicates that educational outcomes are not significantly affected by in utero exposure to natural disasters, but are adversely impacted by exposure during the birth year and the year following. Conversely, health outcomes are significantly influenced by natural disaster exposure both in utero and during infancy.

5.2 Labor Outcomes and Disaster Exposures

Aggregate early-life exposures. The results presented in Table 8 and Table 9 stem from regressions based on Equation 4.1, separately conducted for males and females to examine labor force participation. The regressions incorporate educational and health outcomes to account for the impact of exposure on labor force participation via education and health status. The hypothesis posits that in utero exposure to natural disasters increases the likelihood of long-term diseases, thereby reducing labor force participation in the long run.

Table 8 shows that for females, early-life exposure to natural disasters significantly affects the probability of labor force participation (3.5 and 0.8 percentage points for any type of jobs and jobs paid monthly or annually, respectively). When considering the district-level standardized disaster shock exposures (Table 9), both males and females are significantly negatively affected by the experiences in early life in terms of participation in any type of work and the magnitudes are similar.

Trajectory of early-life exposures. The results presented in Table 10 and Table 11 stem from regressions based on Equation 4.2, separately conducted for males and females to examine labor force participation. While results from considering all types of disasters in EM-DAT show no or weak effects, Table 11 shows that exposure to natural disasters after birth significantly affects the probability of labor force participation for both genders, with a reduction of 6% for males and females. Notably, the disparity between genders is particularly pronounced concerning monthly or annual wage employment (columns (3) and (4)), as opposed to general employment (columns (1) and (2)). These findings reflect the gap depicted in Figure 5a and Figure 5b. Considering the labor market structure, gender norms, and family traditions in India, where female labor force participation rates are significantly lower than those of males, it is unsurprising that being female amplifies these effects. As noted, 36.6% of females aged 15 years and above in rural areas participate in the labor force, compared to 78.2% of males. Female participation in unpaid work is high and is often not recognized as formal work. Almost half of women are involved in domestic duties, child care, goods collection, weaving, and other activities for household use (Fernandez and Puri 2023).

6 Discussion and Conclusion

This study estimates the long-term effects of natural disaster exposures on education, health, and labor force participation in adolescence and early adulthood (age 14 to 40). To conduct this analysis, all disasters occurring from 1970 to 2013 in India were matched by district and year with individuals interviewed in both the first and the second wave of the Indian Human Development Survey (IHDS). This paper is among the few that estimate long-term human capital impacts by considering the cumulative effects of all natural disasters in a specific region or country, rather than focusing solely on in utero or infancy periods. This work complements existing literature on extreme natural disaster shocks and provides new evidence on the broader human capital effects. Additionally, by examining the annual natural disaster exposure history, this work contributes to the literature on climatic shocks before and after the birth year, such as rainfall and droughts (Maccini and Yang 2009; Shah and Steinberg 2017).

The findings reveal that, on average, early-life natural disaster exposures significantly decrease the probability of ever being educated, increase the likelihood of having chronic diseases, and reduce participation in both general work and jobs paid monthly or annually. These effects were identified by exploiting the exogenous variation in the location and timing of natural disasters, as well as the differential exposure of cohorts to these shocks. Furthermore, the analysis of yearly exposure histories that natural disasters occurring during the birth year and the subsequent year (ages 1 to 2) reduce the probability of ever receiving education. In contrast, exposure during the in utero and birth year periods has more pronounced adverse effects on health outcomes, with weak or no corresponding effects from exposure in the following year. The study also finds that early-life exposure to natural disasters negatively affects labor force participation for both genders, with a reduction of 6% for males and 5.3% for females. The disparity in effects is more pronounced for monthly or annual wage employment compared to general employment.

These findings underscore the importance of targeted support for individuals affected by early-life disasters and highlight the need for prevention and mitigation policies to address the long-term consequences of natural disasters. Even in disaster-prone area that have potentially adapted to climate change and developed preparedness strategies for frequent disasters, unexpected disasters of less frequent types or greater intensity can still have significant negative impacts on human capital—a critical factor in economic development. A comprehensive understanding of natural disasters and their effects is essential for designing effective and timely policies to preserve human welfare and mitigate the risks associated with these events.

Tables and Figures

Table 1: Natural disaster characteristics

Disasters	1st quartile	Mean	3st quartile	SD	CV	Skewness	Kurtosis
Flood							
Death	30	269	226	591	2	6	49
Affected	19625	4733700	3000000	12694158	3	6	51
Damage	79516	1112186	821316	2787310	3	5	28
Storm							
Death	21	413	120	1790	4	6	39
Affected	1400	1110382	485910	2764736	2	3	12
Damage	37711	986423	1087599	1748025	2	3	9
Epidemic							
Death	46	330	296	657	2	3	11
Affected	208	10197	6706	27188	3	4	18
Damage							
Extreme temperature							
Death	79	269	286	412	2	4	17
Affected	25	83	112	101	1	1	-2
Damage	452921	514064	575207	172939	0	0	-2
Landslide							
Death	27	87	88	93	1	2	2
Affected	112	225842	7038	643878	3	3	8
Damage	25214	41785	58356	46871	1	0	-2
Earthquake							
Death	18	3107	1357	6396	2	2	2
Affected	444	1781371	502220	5101553	3	3	9
Damage	82827	852675	1265726	1361302	2	2	2
Drought							
Death	90	160	230	198	1	0	-2
Affected	30000000	137310714	250000000	129500164	1	0	-2
Damage	806489	999882	1012024	299896	0	1	-1
Mass movement (dry)							
Death	23	30	38	21	1	0	-2
Affected							
Damage							
Wildfire							
Death	6	6	6				
Affected							
Damage	5634	5634	5634				
Insect infestation							
Death							
Affected							
Damage							

Note: This table shows characteristics of all natural disasters included in EM-DAT dataset for India over 1970-2014. Variable "death", "affected", and "damage" refer to the number of total deaths, number of total people affected, and total economic damages estimated in US dollars (1,000 unit) adjusted by CPI, respectively. Out of 534 events, there are 222 floods, 131 storms, 62 epidemics, 50 extreme temperature events, 38 landslides, 17 earthquakes, 9 droughts, 2 mass movement (dry), 2 wildfires, and 1 insect infestation.

Table 2: Sample overview

	Mean	SD	Min	Max	N
Female	0.45	0.50	0	1	71,922
Age	26.25	8.13	14	40	71,922
Interview year	2012	0.33	2011	2013	71,922
Interview month	5.71	3.00	1	12	71,922
Birth year	1985.64	8.13	1971	1998	71,922
Caste/religion					
Hindu upper caste	0.20	0.40	0	1	71,904
Hindu marginalized caste	0.64	0.48	0	1	71,904
Muslim	0.13	0.34	0	1	71,904
Outcome					
Educ: ever educated	0.84	0.37	0	1	71,867
Health: ever had chronic disease	0.06	0.23	0	1	71,922
Labor: worker of any type	0.61	0.49	0	1	71,922
Labor: salary worker paid monthly or annually	0.12	0.32	0.00	1.00	71,922

Note: This table displays an overview for sample constructed from IHDS dataset.

Table 3: Balance between exposed and non-exposed individuals

Type A: Any disasters in EM-DAT				
	Male		**Female**	
	Mean	SD	Mean	SD
Exposed in period... (%)				
conception to age 2 (early-life)	72.1	44.9	69.5	46.0
in utero	37.4	48.4	35.9	48.0
from birth to age 1	39.9	49.0	38.8	48.7
age 1 to 2	41.0	49.2	39.8	49.0
	Male		**Female**	
*Exposed in **early-life***	Yes	No	Yes	No
Share of people who... (%)				
Educ: ever educated	90.6	88.0	78.9	69.6
Health: ever had long-term disease	3.7	5.0	6.8	9.9
Labor: worker of any type	71.2	85.1	39.8	55.6
Labor: salary worker paid monthly or annually	15.1	21.2	4.6	7.6
Obs	28,418	11,011	22,583	9,910
Type S: District-level standardized disaster shocks				
	Male		**Female**	
	Mean	SD	Mean	SD
Exposed in period... (%)				
conception to age 2 (early-life)	4.3	20.2	4.4	20.5
in utero	0.9	9.5	0.9	9.6
from birth to age 1	1.1	10.3	1.0	10.1
age 1 to 2	1.1	10.2	1.1	10.5
	Male		**Female**	
*Exposed in **early-life***	Yes	No	Yes	No
Share of people who... (%)				
Educ: ever educated	95.5	89.6	93.2	75.3
Health: ever had long-term disease	2.9	4.1	3.2	8.0
Labor: worker of any type	39.1	76.6	25.5	45.5
Labor: salary worker paid monthly or annually	8.2	17.2	1.5	5.7
Obs	1,681	37,748	1,422	31,071

Note: In each of the two panels, this table first presents the distribution of natural disaster exposures in early life by gender, including indicator of exposure from conception to age 2, and the exposure history by year. The second part of the panel presents the distribution of human capital outcomes by natural disaster exposures and genders. For the disaster exposure measure, the top panel presents Type A, and the bottom panel presents Type S. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area. Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as "in shock"). Age range: [14, 40].

Table 4: Effects of disaster exposures on educational and health outcomes (Type A)

	(1) Ever educated	(2) Years of education	(3) Complete low primary sch	(4) Complete upper primary sch	(5) Long-term disease	(6) Cost on long-term disease	(7) Short-term sickness	(8) Cost on short-term sickness
Early-life shock	-0.014***	-0.013	-0.008	0.007	0.005*	0.103	0.001	-0.049
	(0.004)	(0.050)	(0.005)	(0.005)	(0.003)	(0.080)	(0.004)	(0.049)
Female	-0.126***	-1.351***	-0.127***	-0.131***	0.032***	-0.334***	0.066***	-0.130***
	(0.003)	(0.029)	(0.003)	(0.003)	(0.002)	(0.055)	(0.003)	(0.029)
Observations	71849	71835	71835	71835	71903	3886	71903	8931
Caste and religion	Y	Y	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Interview yr FE	Y	Y	Y	Y	Y	Y	Y	Y
Interview mo FE	Y	Y	Y	Y	Y	Y	Y	Y
Age FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table shows regression results corresponding to Equation 4.1. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type A. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area. Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as "in shock"). Age range: [14, 40].

Table 5: Effects of disaster exposures on educational and health outcomes (Type S)

	(1) Ever educated	(2) Years of education	(3) Complete low primary sch	(4) Complete upper primary sch	(5) Long-term disease	(6) Cost on long-term disease	(7) Short-term sickness	(8) Cost on short-term sickness
Early-life shock	-0.011	0.015	0.003	-0.002	0.017***	-0.008	0.013*	-0.071
	(0.012)	(0.139)	(0.012)	(0.013)	(0.004)	(0.183)	(0.008)	(0.078)
Female	-0.126***	-1.351***	-0.127***	-0.131***	0.031***	-0.335***	0.066***	-0.130***
	(0.006)	(0.057)	(0.006)	(0.006)	(0.002)	(0.055)	(0.003)	(0.029)
Observations	71849	71835	71835	71835	71903	3886	71903	8931
Caste and religion	Y	Y	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Interview yr FE	Y	Y	Y	Y	Y	Y	Y	Y
Interview mo FE	Y	Y	Y	Y	Y	Y	Y	Y
Age FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table shows regression results corresponding to Equation 4.1. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type S. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area. Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as ”in shock”). Age range: [14, 40].

Table 6: Effects of disaster exposures on educational and health outcomes (Type A)

	(1) Ever educated	(2) Years of education	(3) Complete low primary sch	(4) Complete upper primary sch	(5) Long-term disease	(6) Cost on long-term disease	(7) Short-term sickness	(8) Cost on short-term sickness
in utero	0.005	0.069*	0.004	0.007*	0.002	-0.010	0.003	0.019
	(0.003)	(0.036)	(0.003)	(0.004)	(0.002)	(0.070)	(0.003)	(0.035)
birth to age 1	0.005	0.033	0.001	-0.001	0.001	0.054	-0.010***	0.009
	(0.003)	(0.036)	(0.003)	(0.004)	(0.002)	(0.070)	(0.003)	(0.035)
age 1 to 2	0.006**	0.101***	0.003	0.005	-0.001	0.024	-0.005	-0.005
	(0.003)	(0.036)	(0.003)	(0.004)	(0.002)	(0.071)	(0.003)	(0.035)
Female	-0.126***	-1.350***	-0.127***	-0.131***	0.032***	-0.336***	0.066***	-0.130***
	(0.003)	(0.029)	(0.003)	(0.003)	(0.002)	(0.055)	(0.003)	(0.029)
Observations	71849	71835	71835	71835	71903	3886	71903	8931
Caste and religion	Y	Y	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Interview yr FE	Y	Y	Y	Y	Y	Y	Y	Y
Interview mo FE	Y	Y	Y	Y	Y	Y	Y	Y
Age FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table shows regression results corresponding to Equation 4.2. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type A. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area. Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as "in shock"). Age range: [14, 40].

Table 7: Effects of disaster exposures on educational and health outcomes (Type S)

	(1) Ever educated	(2) Years of education	(3) Complete low primary sch	(4) Complete upper primary sch	(5) Long-term disease	(6) Cost on long-term disease	(7) Short-term sickness	(8) Cost on short-term sickness
in utero	-0.011	-0.142	-0.011	-0.013	0.019***	0.125	0.030**	-0.124
	(0.017)	(0.195)	(0.016)	(0.017)	(0.007)	(0.418)	(0.013)	(0.163)
birth to age 1	-0.022	-0.126	-0.012	-0.024	0.018**	0.533**	0.015	-0.087
	(0.014)	(0.179)	(0.015)	(0.017)	(0.007)	(0.263)	(0.014)	(0.211)
age 1 to 2	-0.020	-0.082	-0.013	-0.020	0.009	-0.002	-0.002	-0.062
	(0.014)	(0.162)	(0.014)	(0.016)	(0.006)	(0.352)	(0.016)	(0.177)
Female	-0.126***	-1.351***	-0.127***	-0.131***	0.031***	-0.336***	0.066***	-0.130***
	(0.006)	(0.057)	(0.006)	(0.006)	(0.002)	(0.055)	(0.003)	(0.029)
Observations	71849	71835	71835	71835	71903	3886	71903	8931
Caste and religion	Y	Y	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Interview yr FE	Y	Y	Y	Y	Y	Y	Y	Y
Interview mo FE	Y	Y	Y	Y	Y	Y	Y	Y
Age FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table shows regression results corresponding to Equation 4.2. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type S. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area. Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as "in shock"). Age range: [14, 40].

Table 8: Effects of disaster exposures on labor force participation (Type A)

	Worker of any type		**Salary worker paid monthly or annually**	
	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Early-life shock	-0.005	-0.035^{***}	0.004	-0.008^{*}
	(0.005)	(0.008)	(0.007)	(0.005)
Educ: ever attended school	-0.017^{***}	-0.126^{***}	0.101^{***}	0.044^{***}
	(0.005)	(0.007)	(0.006)	(0.003)
Have or had long-term disease	-0.088^{***}	-0.024^{**}	-0.014	-0.004
	(0.010)	(0.010)	(0.009)	(0.005)
Observations	39377	32472	39377	32472
Caste and religion	*Y*	*Y*	*Y*	*Y*
District FE	*Y*	*Y*	*Y*	*Y*
Interview yr FE	*Y*	*Y*	*Y*	*Y*
Interview mo FE	*Y*	*Y*	*Y*	*Y*
Age FE	*Y*	*Y*	*Y*	*Y*

Note: This table shows regression results corresponding to Equation 4.1. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type A. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area. Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as "in shock"). Age range: [14, 40].

Table 9: Effects of disaster exposures on labor force participation (Type S)

	Worker of any type		**Salary worker paid monthly or annually**	
	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Early-life shock	-0.060^{***}	-0.053^{**}	-0.005	-0.016^{**}
	(0.018)	(0.021)	(0.013)	(0.007)
Educ: ever attended school	-0.017^{**}	-0.126^{***}	0.101^{***}	0.044^{***}
	(0.007)	(0.010)	(0.007)	(0.004)
Have or had long-term disease	-0.088^{***}	-0.024^{**}	-0.014	-0.003
	(0.010)	(0.010)	(0.009)	(0.005)
Observations	39377	32472	39377	32472
Caste and religion	Y	Y	Y	Y
District FE	Y	Y	Y	Y
Interview yr FE	Y	Y	Y	Y
Interview mo FE	Y	Y	Y	Y
Age FE	Y	Y	Y	Y

Note: This table shows regression results corresponding to Equation 4.1. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type S. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area. Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as ”in shock”). Age range: [14, 40].

Table 10: Effects of disaster exposures on labor force participation (Type A)

	Worker of any type		**Salary worker paid monthly or annually**	
	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
in utero	-0.002	-0.005	0.007^{*}	0.003
	(0.005)	(0.006)	(0.004)	(0.003)
birth to age 1	0.003	0.010^{*}	0.010^{**}	0.003
	(0.005)	(0.006)	(0.004)	(0.003)
age 1 to 2	-0.000	0.005	0.005	0.002
	(0.005)	(0.006)	(0.004)	(0.003)
Educ: ever attended school	-0.017^{***}	-0.126^{***}	0.101^{***}	0.044^{***}
	(0.005)	(0.007)	(0.006)	(0.003)
Have or had long-term disease	-0.088^{***}	-0.025^{**}	-0.014	-0.004
	(0.010)	(0.010)	(0.009)	(0.005)
Observations	39377	32472	39377	32472
Caste and religion	*Y*	*Y*	*Y*	*Y*
District FE	*Y*	*Y*	*Y*	*Y*
Interview yr FE	*Y*	*Y*	*Y*	*Y*
Interview mo FE	*Y*	*Y*	*Y*	*Y*
Age FE	*Y*	*Y*	*Y*	*Y*

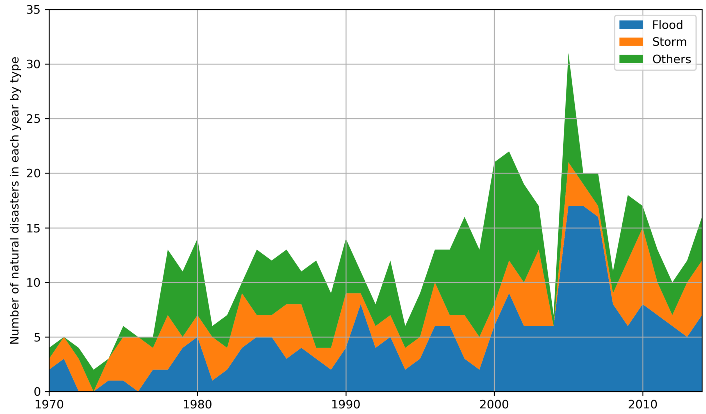
Note: This table shows regression results corresponding to Equation 4.2. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type A. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area. Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as ”in shock”). Age range: [14, 40].

Table 11: Effects of disaster exposures on labor force participation (Type S)

	Worker of any type		**Salary worker paid monthly or annually**	
	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
in utero	-0.045	-0.053	-0.011	-0.015
	(0.032)	(0.034)	(0.019)	(0.010)
birth to age 1	-0.058^{**}	-0.010	-0.002	-0.005
	(0.028)	(0.033)	(0.017)	(0.009)
age 1 to 2	-0.049^{*}	-0.059^{**}	-0.015	-0.015^{**}
	(0.028)	(0.029)	(0.019)	(0.006)
Educ: ever attended school	-0.017^{**}	-0.126^{***}	0.101^{***}	0.044^{***}
	(0.007)	(0.010)	(0.007)	(0.004)
Have or had long-term disease	-0.088^{***}	-0.024^{**}	-0.014	-0.004
	(0.010)	(0.010)	(0.009)	(0.005)
Observations	39377	32472	39377	32472
Caste and religion	*Y*	*Y*	*Y*	*Y*
District FE	*Y*	*Y*	*Y*	*Y*
Interview yr FE	*Y*	*Y*	*Y*	*Y*
Interview mo FE	*Y*	*Y*	*Y*	*Y*
Age FE	*Y*	*Y*	*Y*	*Y*

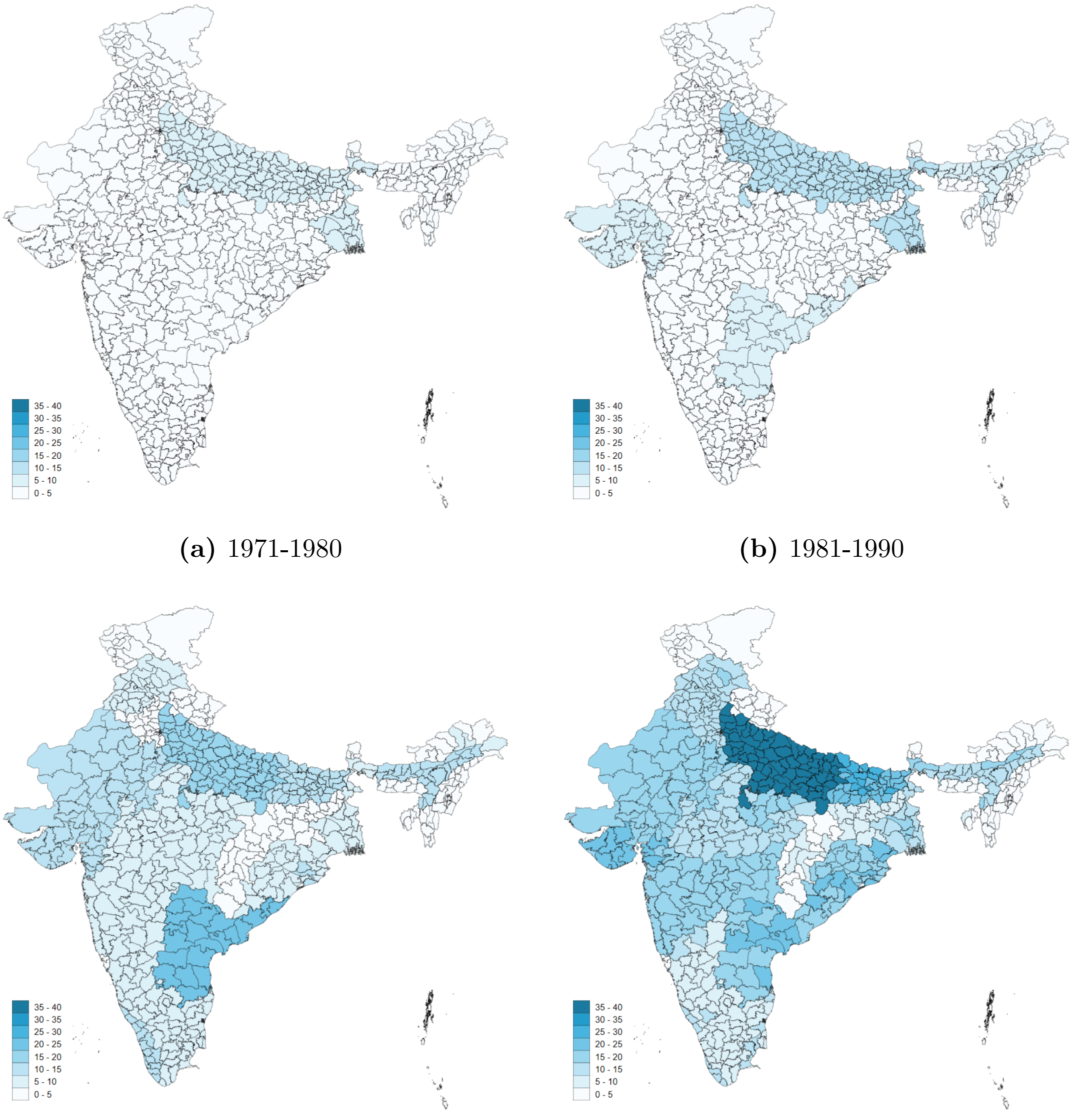
Note: This table shows regression results corresponding to Equation 4.2. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type S. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area. Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as "in shock"). Age range: [14, 40].

Fig. 1. Number of natural disasters in India 1970-2014



Note: This considers all natural disasters regardless of the type and intensity recorded in EM-DAT data in India from 1970 to 2014.

Fig. 2. Number of natural disasters (EM-DAT record) for each district in 10 years



(a) 1971-1980

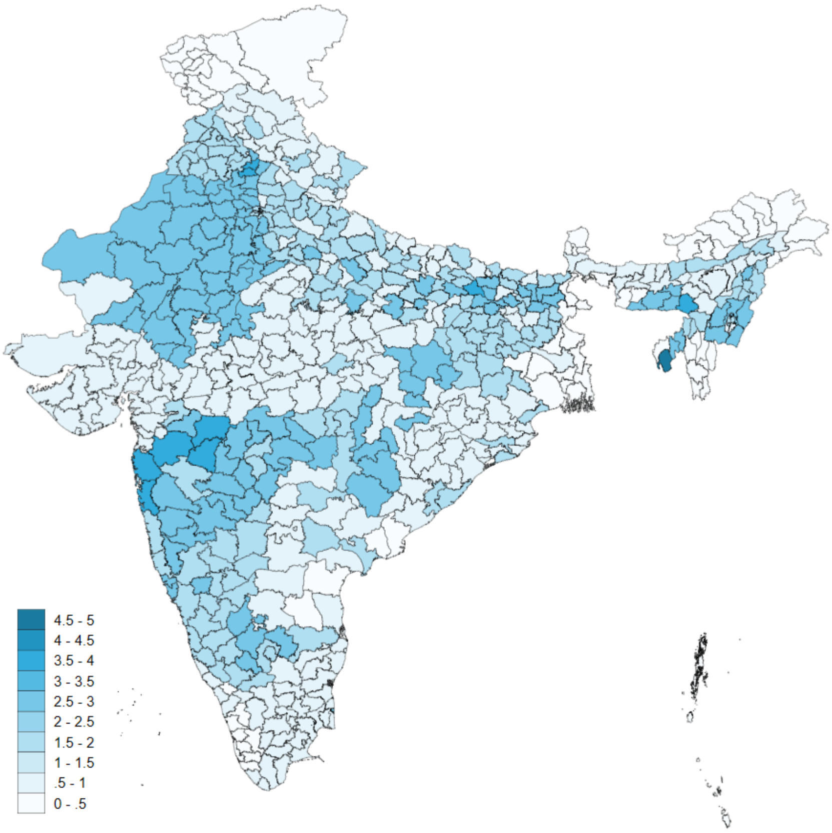
(b) 1981-1990

(c) 1991-2010

(d) 2001-2010

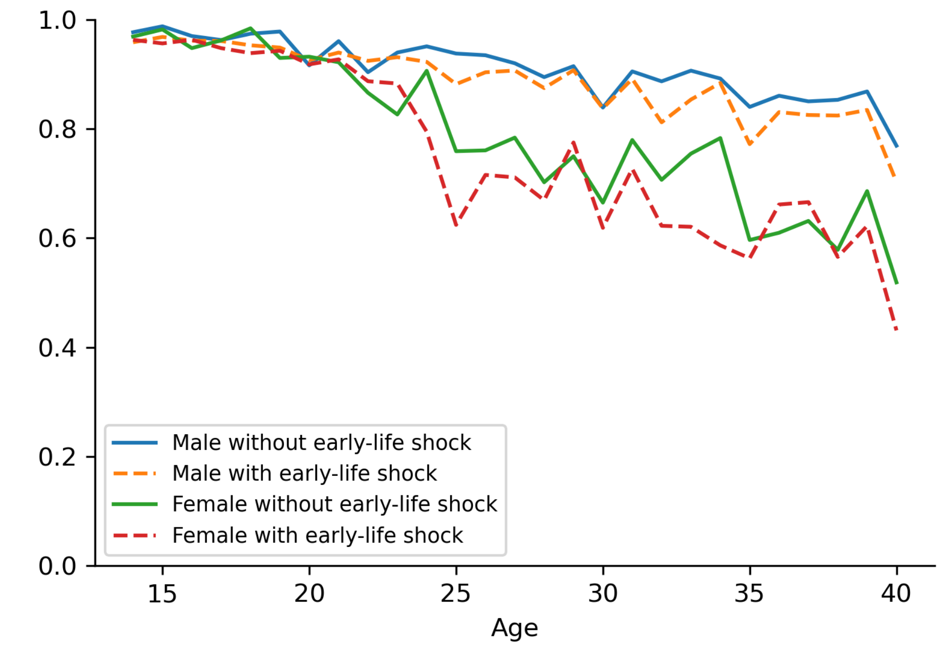
Note: This figure shows the number of natural disasters recorded in EM-DAT experienced by each district in a 10-year window from 1971. This corresponds to Type A disaster exposure measure. Type A measure of natural disaster exposures is an indicator considering all events recorded in EM-DAT. It is 1 if the district in certain year has been recorded as affected area.

Fig. 3. Number of years in natural disaster shocks by districts in 2001-2010

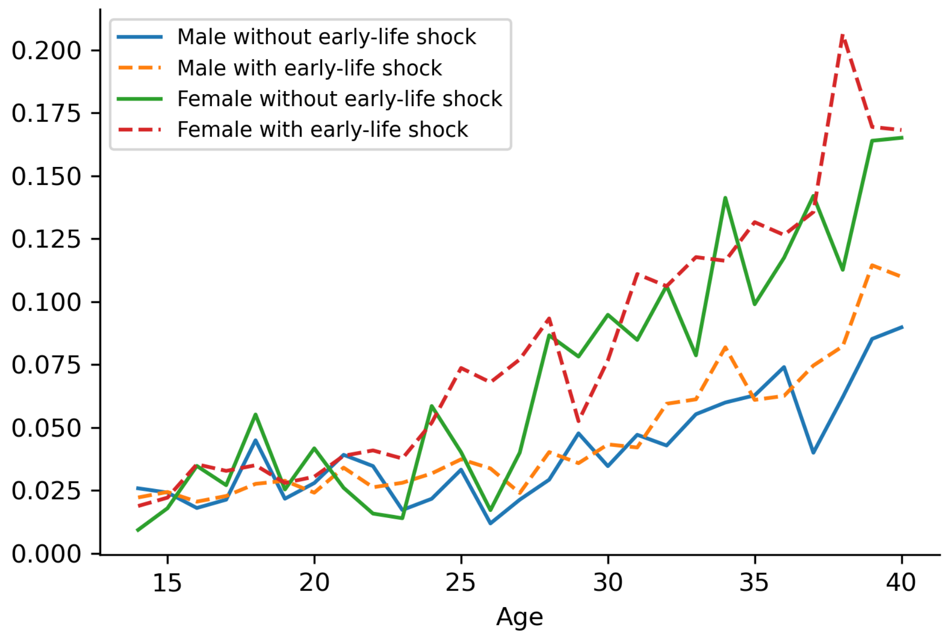


Note: This shows the number of years in natural disaster shocks (type S). Type S measure of natural disaster exposures is an district-year specific indicator. It is standardized at district level. It is 1 if the number of disasters occurring in certain year exceeds the mean by 2 SD of number of disasters that happened in certain district over 1971-2013 (this district-year is defined as "in shock"). The average number of years in shock for all districts in 10 years are 0.01, 0.05 0.29, and 1.58 in 1971-1980, 1981-1990, 1991-2000, 2001-2010.

Fig. 4. Distribution of human capital outcomes over ages



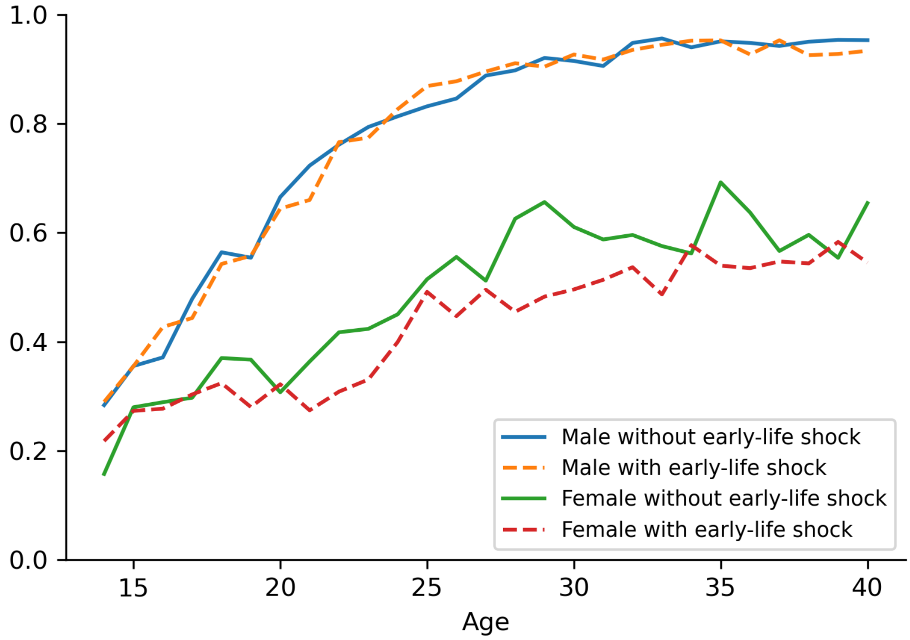
(a) Share of people ever educated



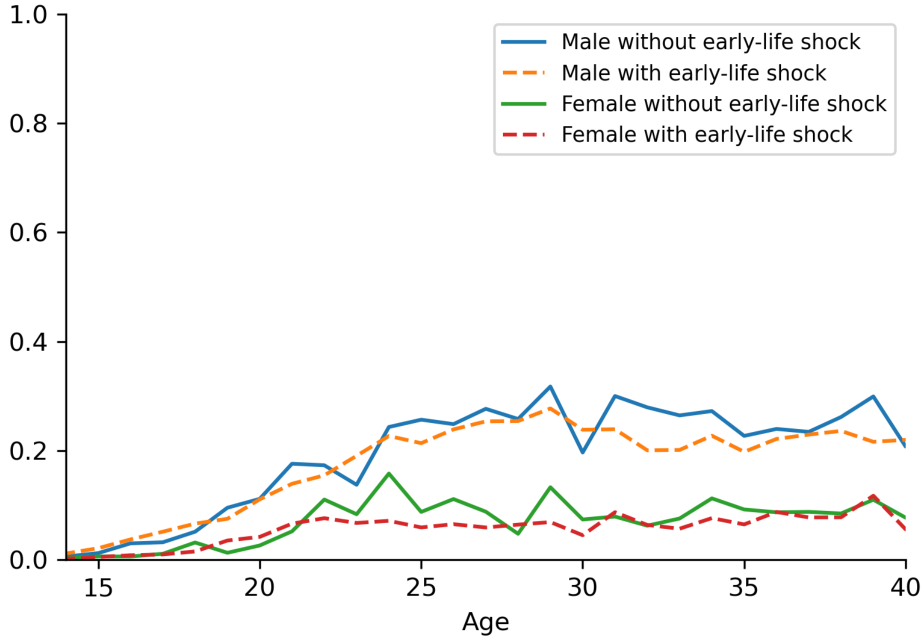
(b) Share of people ever with chronic disease

Note: The distribution is not conditional on any factors. Here early-life shock refers to "having experienced any natural disasters since conception to age 2."

Fig. 5. Distribution of human capital outcomes over ages



(a) Share of people working for any type



(b) Share of people working for salary paid monthly or annually

Note: The distribution is not conditional on any factors. Here early-life shock refers to "having experienced any natural disasters since conception to age 2."

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