The Long-Term Human Capital Consequences of 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 the India Human Development Survey (IHDS) by the district and cohort, 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 lead 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.

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). Also, for specific type of disaster, there may be specific way to increase the resilience or adaptation, although how powerful the methods can be needs investigation. For example, reservoirs can mitigate the effects from droughts (DePaula, Jeddi, and Keiser 2024), expediting the restoration of disrupted utilities can improve the electricity system resilience against hurricanes (Asadi et al. 2024), local governments respond to hurricane impact by raising tax rates (Mateen 2024), and consumer behavior and household demand in healthcare can be adapted to wildfire smoke (Han, Li, and Wang 2023). Capturing the real shocks for locations during certain time and understanding how regions cope with such shocks hence become questions. However, research on the effects of natural disasters during critical developmental periods is limited, particularly concerning resilience and preparedness.

Short-term interruptions can lead to long-term effects of disaster exposure on human capital development and accumulation. Adverse conditions in early life, especially the critical period for human capital development from conception to age 2 or before primary school, may have enduring impacts. A growing body of literature documents the lasting effects of early childhood shocks on child development (Currie 2009; Andrabi, Daniels, and Das 2021) 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 adolescence and 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? If the effects exist, what are potential heterogeneities across gender, age, or socio-economic status? Understanding how these exposures impact vulnerable groups is essential for crafting effective policies to enhance resilience and reduce poverty. To estimate these impacts, I use the panel sample from Indian Human Development Survey (IHDS) and EM-DAT International Disaster Database to link individuals in adolescence and early adulthood to all time- and geo-coded natural disasters occurring in India during their individual-specific life history. Eventually, more than 71,000 individuals who are aged 14 to 40 when interviewed in 2011-2013 are linked to over 500 natural disasters that have led to substantial loss of human life in India between 1970 and 2013.

I conduct individuals' exposure to natural disasters in early life and provide the all-natural-disaster-inclusive analyses of effects of natural disaster exposures on human capital in the long run. For each child, the binary indicators of if she has been experienced any disaster shocks as well as the yearly trajectories of disaster shock experiences in her early life are constructed. The disasters linked to individuals in the sample include floods, storms, epidemics, extreme temperatures, landslides, earthquakes, droughts, etc. I consider two type of disaster shock measures, of which one is capturing the level of district- and year-specific experience, a binary variable being one if the district in this year has experienced any disasters. The other one is constructed considering the standard deviation at the district-level, to capture the preparedness of locations to the location-specific natural disaster history and gauge the magnitude of shocks experienced by a district within a year. Specifically, I analyze the deviation in the number of disasters occurring annually in each district. I calculate the number of disasters for each district in each year and the mean and standard deviation of the number of disasters experienced by each district from 1970 to 2014. Then, 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".

Exploiting variations in survey locations, variations in location-specific survey timing, as well as age variations among individuals surveyed in each location and each year, I investigate the impacts of exposure histories to natural disasters on human-capital accumulation, including educational outcomes, health outcomes, and labor force participation. Existing literature has found that natural disaster shocks experienced in utero can cause changes in prenatal stress (Andrabi, Daniels, and Das 2021; Charil et al. 2010; Fuller 2014). Given the potential serial correlation of natural disasters over time, events experienced in the years surrounding the birth year may also 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. Besides, 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). Children and young adults could experience poorer health and educational outcomes in the long run if exposed to adverse prenatal and postnatal environments (Almond, Currie, and Duque 2018). Due to negative health and economic impacts, for example, changes in prenatal stress caused by natural-disaster exposures have negative impacts on educational and economic performance later in life (Andrabi, Daniels, and Das 2021; Charil et al. 2010; Fuller 2014). Therefore, the early life in this study is focused and investigated as the period from conception to the age 2 (the first 1,000 days), which has been found to be closely related to human capital and strongly emphasized in the literature on nutrition as well as other dimensions of human development (Behrman and Hoddinott 2005; Doyle 2020; Grantham-McGregor et al. 2007; Hoddinott et al. 2008; Hoddinott et al. 2013; Gertler et al. 2014; Black et al. 2022; Victora et al. 2008; Victora et al. 2010).

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. When all disasters recorded in EM-DAT are considered for disaster exposures, individuals who have been exposed in early life show a 1.4 percentage point reduction in the probability of having received any education, and females are affected more negatively compared to males. Females are also more adversely affected in terms of having long-term disease by early life exposures. The investigation in trajectory of early-life exposures shows that in utero or infancy exposures do not shape later-life educational and health outcomes as much as the year from age 1 to 2. These results are robust for both types of natural disaster exposure measures for educational and health outcomes. In terms of labor force participation, the measures capturing the district- and year-specific standard deviation of disaster shocks show that exposures after birth significantly affect the probability of participation for both genders. Meanwhile, the disparity between genders is particularly pronounced concerning monthly or annual wage employments.

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 Natural Disasters

The natural-disaster variables are derived from the EM-DAT International Disaster Database (Delforge et al. 2023). Compiled by the Centre for Research on the Epidemiology of Disaster (CRED), EM-DAT 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 examined using panel data of European firms and EM-DAT (Leiter, Oberhofer, and Raschky 2009). It is also used to estimate the association between price flexibility and vulnerability to disaster risk shocks (Isoré 2018). EM-DAT is also used to identify the severity of natural disaster events and further estimate the effects of natural disasters on human capital accumulation such as schooling and health status (Caruso 2015; Caruso 2017), growth retardation (Thamarapani 2021), poverty and well-being (Edmonds and Noy 2018), human activities such as youth migration (Baez et al. 2017), consumption adversities (Eskander and Barbier 2022).

With 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.

2.2 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).

2.3 Disaster Exposure Measures

There are multiple ways to define the individual exposures to natural disasters. All the ways can be categorized into two broad groups. One group is linking the geo- and time-coded disasters shocks with the individuals residing in certain locations during certain periods, while the other group is using the disaster experience related questions in surveys to construct the measures of disaster exposures.

For example, for individuals who were recorded residing (or being born) in the one district Kupwara in year 1990, and there was one flood recorded affecting this district, then we can assign a binary variable to them indicating if they were exposed to any disaster or not. This has been used in (Wang, Yang, and Li 2017). Some papers studying the effects of earthquakes go beyond identifying if one has experienced any disasters. For example, those investigating one single but usually large event use the distance of district (or any geo-location) to the epicenter or fault line of the earthquake to construct the exposure intensity (Andrabi, Daniels, and Das 2021; Cameron and Shah 2015; Tian, Gong, and Zhai 2022), or accumulated scales of earthquakes (Bai and Li 2021), or the quake level to measure seismic risk shocks (Bai 2023). Those investigating more than one events specify the frequency and intensity of events, which can be calculated from the distribution of occurrence of disasters (Huang, Liu, and Tang 2024), the total value of material damages (Bertinelli, Mahé, and Strobl 2023; Cameron and Shah 2015; Huang, Liu, and Tang 2024), or use the Mercalli scale and Richter scale of earthquakes (Caruso and Miller 2015).

The second group of studies aiming to avoid the measurement error on identification of object to study affected by the disaster, do not rely on the location and ask the experience of the firms directly in survey. This potentially captures the actual damage of disasters which depend

1. A third wave is currently in the field.

on more than the location including factors like the state of maintenance, the obsolescence of the production structure of firms, and more localized government support (Antonioli, Marzucchi, and Modica 2022). Surveys on individuals may also ask about the experience with natural disasters or extreme weather events, like like UNICEF Multiple Indicator Cluster Survey (MICS) 6th wave (UNICEF 2010) and Young Lives (McQuade and Favara 2024; Nguyen and Minh Pham 2018). One potential disadvantage of this type of measures is that survey may not capture the experience that happens long time before the interview date due to faint memories, and it is almost impossible to retrieve the shocks during one's early life. A few papers combine both ways to measure natural disaster exposures (Cameron and Shah 2015).

In this study, I use the first type of strategies to construct district-level disaster exposure measures and merge them to individuals by districts and years to identify individual-level age-specific disaster exposures.

2.3.1 District-Year Disaster Exposures

In EM-DAT, all locations at first-level and second-level administrative divisions affected by one disaster are listed. This means that in the case of India, the location names can be state or district, and if it is state recorded, it indicates that entire state has been affected by that event. As it is also observed the district (the second-level administrative locations) individuals reside in IHDS, I am able to link disasters with each location in the IHDS data. I use 2001 Indian division to specify the states and districts linkage. Jointly using the starting and ending dates of each disasters, I first create a district-level yearly panel dataset recording for each district d at each year t number of disasters occurred, ND_{dt}. Then, type A and S measures of disaster exposures are constructed also at district-year base.

Type A: Any disasters in EM-DAT. For each district-year, an indicator is created showing if any disaster occurred, denoted by $ID_{dt,A}$, being one if district d in year t has been exposed to type A disasters:

$$ID_{dt,A} = \mathbf{1}\{ND_{dt} > 0\} \tag{2.1}$$

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. While the type A disaster exposure measures capture the overall "level" of disaster experience, they may not fully account for variability in disaster impact across regions. Certain areas are more disaster-prone, as shown in Figure 2, and as regions become more resilient or adapt to disaster shocks, there may be less fluctuation in the number of people affected if we only rely on the type A exposure measures. In studies examining rainfall shocks and their effects on human capital, shocks are sometimes defined as deviations from the location-specific rainfall norm in a given year (Maccini and Yang 2009). Following this approach, I develop the type S measure to capture district-specific deviations from the norm, reflecting the intensity of shocks experienced by each district annually.

Using the number of disasters ND_{dt} for each district d in year t, I calculate the mean and standard deviation of the number of disasters experienced by district d from 1970 to 2014, denoted by $\mu_{d,1970-2014}$ and $\sigma_{d,1970-2014}$, respectively. Then, if in any given year, the number of disasters experienced by a district exceeds its mean by two standard deviations, the corresponding year is labeled as "experiencing disaster shock" for that district by an indicator $ID_{dt,S}$ being one and zero otherwise:

$$ID_{dt,S} = \mathbf{1}\{ND_{dt} > \mu_{d,1970-2014} + 2 \times \sigma_{d,1970-2014}\} \tag{2.2}$$

2.3.2 Cohort-Age Disaster Exposures

Using the district-year panel dataset, along with the interview year-month and birth year (or age) of individuals in IHDS, I generate a cohort-level yearly dataset recording for each birth cohort at each age-in-year whether they are exposed to disasters. Specifically, in this cohort-age data, I construct disaster exposure, $D^J_{dc,p\in\{A,S\}}$, for cohort c in district d at age J, measuring if they have been exposed to type p disaster shock.

Furthermore, this cohort-age panel dataset allows me to divide one cohort's life into segments. I aggregate over the period from year before birth year (in utero), birth year, year at age 1, and year at age 2, to generate the indicator of early-life disaster exposure measure, $D_{dc,EarlyLife}$.

2.4 Human Capital Measures

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.

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.[2]

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

2. 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.

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).[3] Extreme temperature events, including cold waves (28 events), heat waves (20 events), and severe winter 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 or 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. 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

3. 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.

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

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. 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 2.4.

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, suggesting potential 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 the 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:

$$Y_{idc} = \alpha + \beta \cdot D_{dc,EarlyLife} + X_i'\theta + \mu_d + \phi_c + \epsilon_{idc}, \tag{4.1}$$

where Y_{idc} represents the human capital measures for individual i residing in district d, of birth cohort c. $D_{dc,earlyLife}$ is the disaster exposure measure in district d for birth cohort c during their early life. The vector X_i' includes individual-specific control variables such as age, gender, caste and religion, interview year and month. The model includes a vector of district fixed effects μ_d to account for unobserved heterogeneity at the district level, which are at the same (or lower) level of geographical aggregation as the disaster variables. Cohort fixed effects ϕ_c are also incorporated. The error term ϵ_{ilty} is assumed to be random and idiosyncratic, with standard errors clustered at the district level. Exposures to early life shocks have been found to have large effects on later-life health and educational outcomes due to prenatal stress and nutrition conditions (Maccini and Yang 2009; Dimitrova and Muttarak 2020; Skoufias and Vinha 2012; Thai and Falaris 2014; Rosales-Rueda 2018). Under the assumption that individuals' information is collected in or they reside in the district where they are born, this regression estimates the effects of early life shocks human capital outcomes in later life.

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:

$$Y_{idc} = \alpha + \sum_{J \in TimeSpan} \beta_J \cdot D_{dc}^J + X_i'\theta + \mu_d + \phi_c + \epsilon_{idc}, \tag{4.2}$$

where Y_{ibc} still represents the human capital measures for individual i in district d, from birth cohort c. D_{dc} represents the natural disaster exposures of district d for birth cohort c, while $TimeSpan$ includes the periods $\{inUtero, birthYear, age1, age2\}$; the coefficients β_J hence 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.

I assume that individuals' information is collected in or they reside in the district where they are born, and restrict the sample using several piece 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% have not migrated.[4] Third, both IHDS-I and IHDS-II ask about migration history at household level. For all the households included in IHDS-II, 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.[5]

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

4. 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.

5. 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", 57 households lack this information. For the rest 9,266 households, the "years in current place" is recorded with a number less than 90, and their place of origin is recorded in these categories: "same state, same district"—5,059 households (12% of all IHDS-II households), "same state, another district"—2,122 (5%) households, "another state"—1,398 (3%) households, "another country"—646 (1.5%) households, "missing"—41 households.

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	276	225	612	2	6	46
Affected	15,000	4,857,821	3,000,000	12,979,584	3	6	49
Damage	70,097	964,658	901,369	2,018,760	2	5	27
Storm							
Death	23	448	117	1,901	4	6	34
Affected	2,000	1,197,424	485,910	2,882,593	2	3	10
Damage	37,254	814,315	872,438	1,270,169	2	2	4
Epidemic							
Death	46	298	296	578	2	4	15
Affected	205	11,095	5,642	28,942	3	4	16
Damage							
Extreme temperature							
Death	82	285	275	443	2	4	15
Affected	25	25	25	0	0		
Damage	471,566	535,226	598,885	180,057	0	0	-2
Mass movement (wet)							
Death	26	87	87	96	1	2	2
Affected	92	239,945	8,850	662,277	3	3	7
Damage	26,252	43,505	60,758	48,800	1	0	-2
Earthquake							
Death	23	3,313	1,404	6,564	2	2	2
Affected	5,712	1,900,127	526,547	5,257,667	3	3	8
Damage	134,238	984,871	1,560,239	1,467,614	1	2	2
Drought							
Death	90	160	230	198	1	0	-2
Affected	62,500,000	158,529,167	275,000,000	127,837,710	1	0	-2
Damage	962,499	1,091,380	1,175,945	336,302	0	0	-1
Wildfire							
Death	6	6	6				
Affected							
Damage	5,866	5,866	5,866				
Mass movement (dry)							
Death	16	16	16				
Affected							
Damage							

Note: This table shows characteristics of natural disasters events. 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. 517 events are recorded in EM-DAT database for India over 1970-2013. 480 events are mapped to locations (93%) based on the information "area affected". These include 205 floods, 117 storms, 53 epidemics, 42 extreme temperature events, 35 mass movement (wet) or landslides, 16 earthquakes, 9 droughts, 2 wildfires, 1 mass movement (dry), and 1 infestation. No data on death, affected, or damage are recorded for the infestation event.

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: Education					
Ever attended school	0.84	0.37	0	1	71,867
Years of education (never=0)	7.66	4.52	0	15	71,853
Lower primary school completed	0.77	0.42	0	1	71,853
Upper primary school completed	0.67	0.47	0	1	71,853
Secondary school completed	0.26	0.44	0	1	71,853
High school graduate	0.12	0.32	0	1	71,853
Outcome: Health					
Have or had long-term disease	0.06	0.23	0	1	71,922
Health expenditure for long-term disease (log)	8.44	1.62	0	12.95	3,908
Sick in last mo. (diarrhea, fever, cough)	0.13	0.34	0	1	71,922
Health expenditure for short term sickness (log)	5.43	1.39	0	11.03	8,937
Outcome: Labor					
Worker of any type	0.61	0.49	0	1	71,922
Salary worker paid monthly or annually	0.12	0.32	0	1	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... (%)				
from 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
Observations	28,418	11,011	22,583	9,910

Type S: District-level standardized disaster shocks				
	Male		**Female**	
	Mean	SD	Mean	SD
Exposed in period... (%)				
from 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
Observations	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*

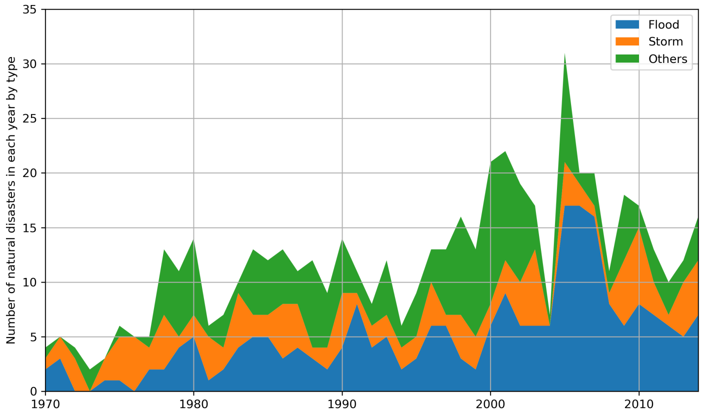
Note: This table shows regression results corresponding to Equation 4.2. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type 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*

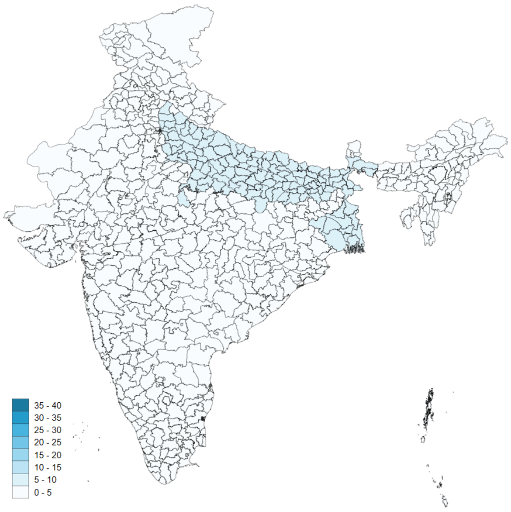
Note: This table shows regression results corresponding to Equation 4.2. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. Disaster exposure measure: Type 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

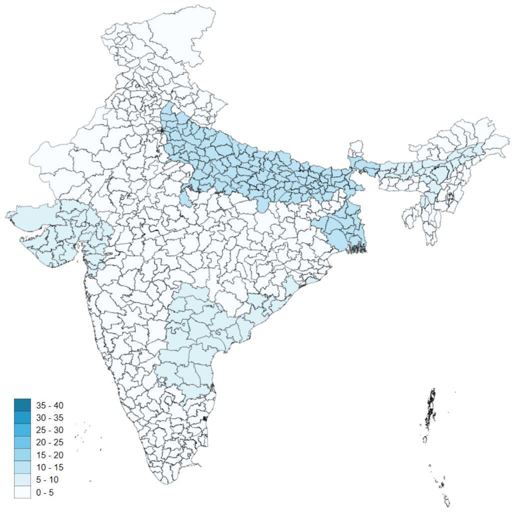


Note: This considers all natural disasters regardless of the type and intensity recorded in EM-DAT data in India from 1970 to 2014.

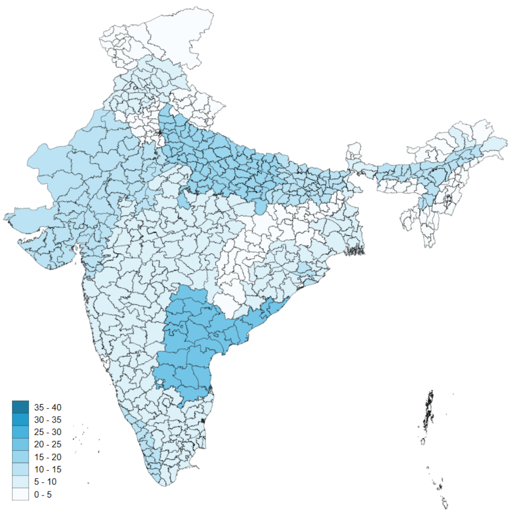
Fig. 2. Number of natural disasters (EM-DAT record) for each district in 10 years



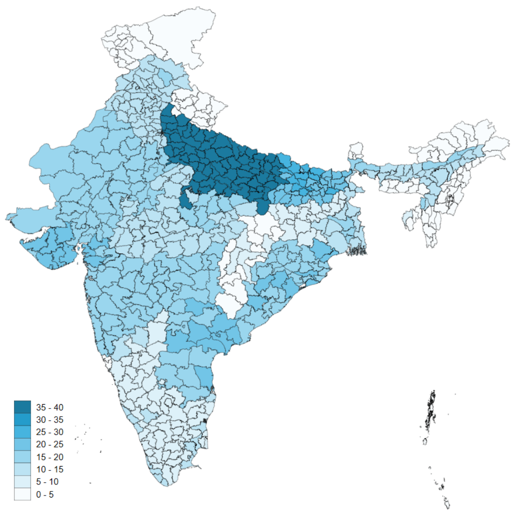
(a) 1971-1980



(b) 1981-1990



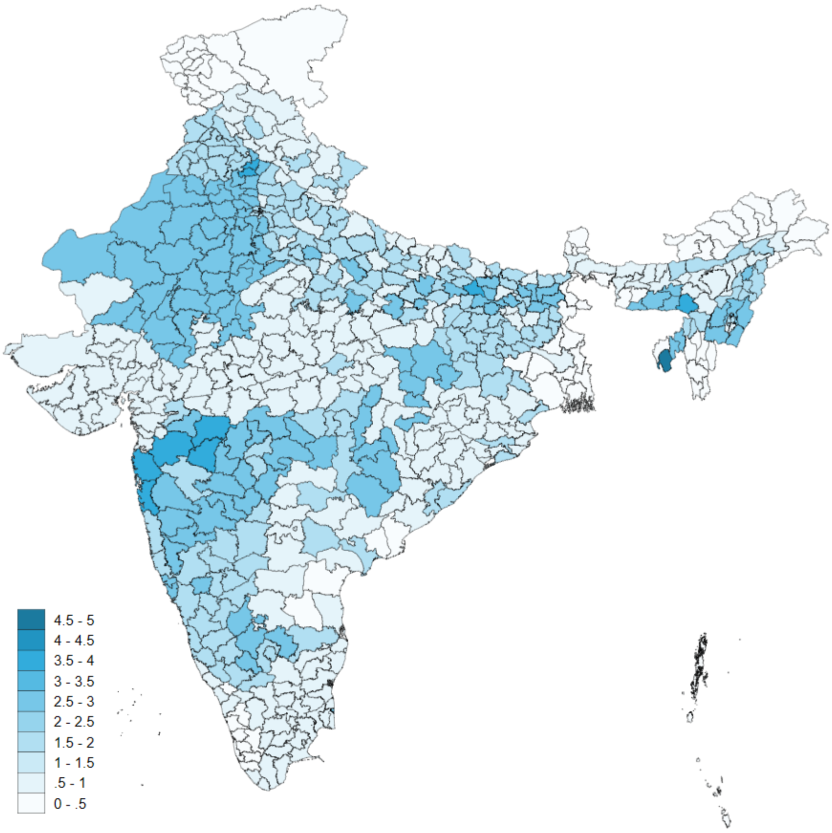
(c) 1991-2010



(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.

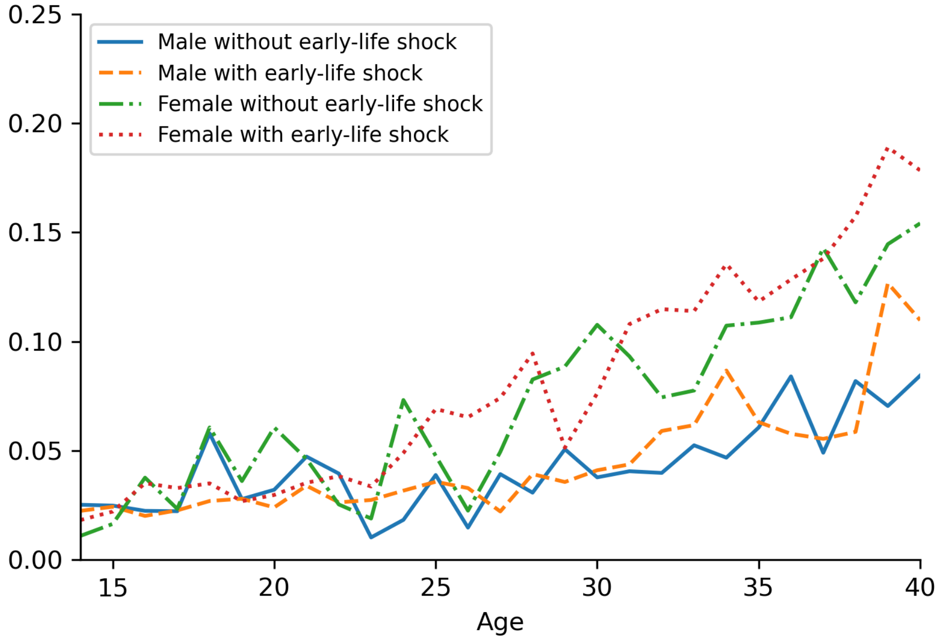
Fig. 3. Number of years in natural disaster shocks by districts in 2001-2010



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

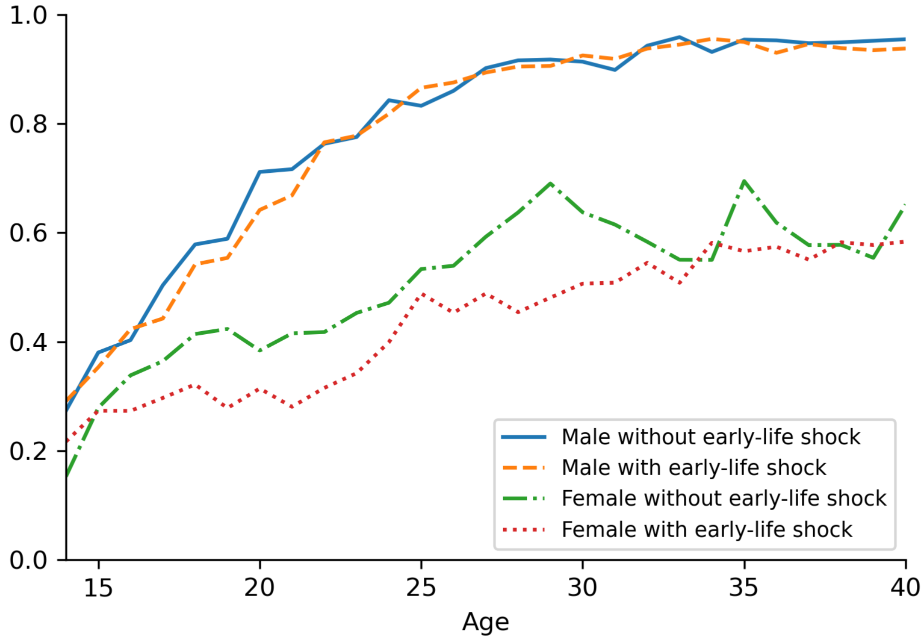
(a) Share of people ever educated



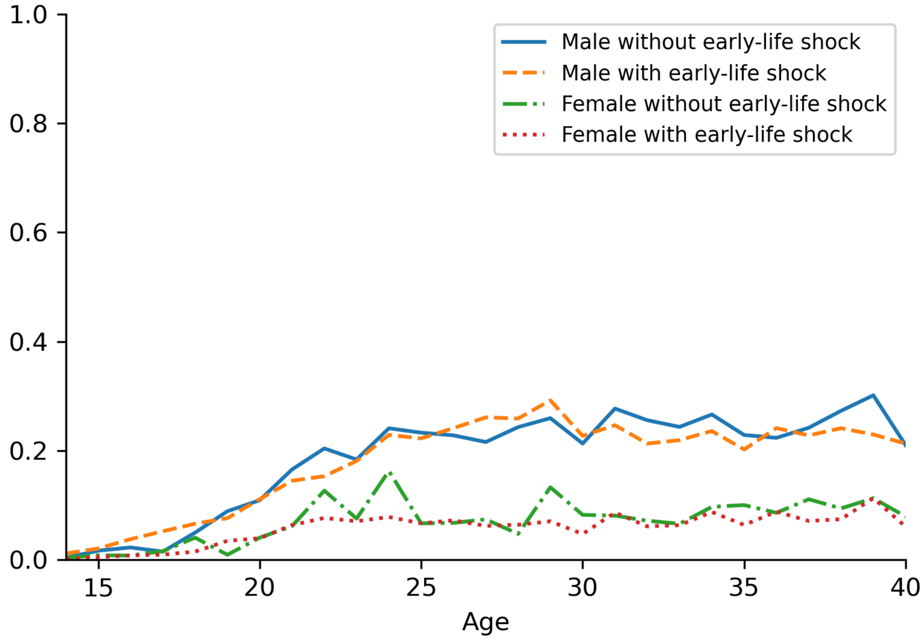
(b) Share of people ever with long-term disease

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 job



(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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