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

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Abstract

This paper examines the long-term effects of early-life exposure to natural disasters on human capital during adulthood. It is the first to study this question considering the frequency and severity of multiple disaster events—a vital focus as climate change accelerates the occurrence and intensity of natural disasters. Based on "the number of people affected per 100 population", I categorize events as severe or non-severe and link about 500 natural disasters in India from the EM-DAT database with nationally representative data from the India Human Development Survey (IHDS). I construct a sample of over 59,000 individuals aged 20 to 40 to explore the effects of disaster exposure from in utero to age 2 on educational attainment, health outcomes, and labor market participation. Exploiting geographical and temporal variations in disaster exposure, the results reveal significant adverse effects of early-life disaster exposures on human capital, predominantly driven by severe disasters. Exposure to more severe disasters in early life lowers educational attainment for both men and women, and lower labor force participation in general and formal employment for men. Women exposed to severe disasters in early life display a lower incidence of long-term disease in adulthood, suggesting a gender-specific survival bias.

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).

There is significant variability in the impacts of natural disasters, making it challenging yet meaningful to measure their effects while accounting for both the frequency and severity of events. For instance, it is difficult to determine whether multiple floods, each displacing 10 people in a village, are more severe than a single flood displacing 100 people in a state in total at once. 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 group of literature documents the lasting effects of early childhood shocks on fatal loss and child development (Currie 2009; Andrabi, Daniels, and Das 2021; Lin and Liu 2014; Liu, Liu, and Tseng 2022a) as well as on adulthood outcomes such as education, health, and socioeconomic status (Alderman, Hoddinott, and Kinsey 2006; Almond 2006; Rosales-Rueda 2018; Maluccio et al. 2009; Liu, Liu, and Tseng 2022b). However, there is fewer research on the impact of natural disaster exposures 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 early-life exposure to natural disasters on human capital during adulthood? What kinds of natural disasters drive the effects, if any, in terms of the frequency and severity of natural disaster shocks? Does the timing or age at which early-life exposure occurs influence the magnitude of these effects? 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 a nationally representative data, Indian Human Development Survey (IHDS), and natural disaster records from EM-DAT International Disaster Database to link adult individuals to all time- and geo-coded natural disasters occurring in India during their early-life. Using the information from about 500 natural disasters that have led to substantial loss of human life in India between 1970 and 2013, I generate the district-cohort disaster exposure measures in early life. Linking them to more than 59,000 individuals who are aged 20 to 40 when interviewed in 2011-2013, I analyze their effects on human capital in the long run.

For all the disasters such as floods, storms, epidemics, extreme temperatures, landslides, earthquakes, droughts, I conduct a measure, "number of people affected per 100 population", to identify if one disaster event is severe or not. This is calculated as dividing the number of people affected by one disaster by the residing population in the area affected. Hence, I consider two type of disaster exposure measures, of which one considers all natural disasters from EM-DAT database, and the other one includes only the severe disasters. While this measure captures the severity of disaster events, I estimate the effects of number of any disaster (non-severe and severe events) as well as the number of only severe events one individual is exposed to, to capture and compare the effects of severity and frequency of natural disaster shocks. Specifically, I calculate the number of natural disaster events one individual has been exposed to in utero year, birth year, year at age 1, and year at age 2.

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).

The results reveal negative effects of disaster exposure on educational attainment and labor force participation, irrespective of wage employment status. When all disaster events recorded in EM-DAT are considered, the effects are weak or statistically insignificant. However, exposure to severe disaster events demonstrates persistent and significant impacts. Individuals exposed to one additional severe disaster event in early life receive, on average, 0.147 fewer years of education (approximately 1.8 months). For those exposed to the most severe disasters—four events—early-life exposure is associated with a loss of approximately 7 months of education compared to those unexposed, accounting for 8% of the average years of education completed. The effects are strong and persistent across gender, but particularly pronounced for women. Women exposed to disasters in early-life are found to be healthier in terms of lower probability of having long-term disease. Women exposed to one more severe disaster event in early life face a 0.6 percentage point lower probability of having long-term disease, suggesting a gender-specific survival bias. In terms of labor force participation, women exposed to one more disaster event show 1.3 percentage point rise in the probability of working for any job. Men are particularly worse off if they have been exposed to severe disasters in early life. Being exposed to one more severe disaster lowers the probability of working full-time for a salary position by 1.2 percentage point, which is 7.5% decrease for men. The investigation in early-life exposures by years shows that the birth-year exposures to disasters shape later-life educational and health outcomes as much as the year from age 1 to 2. These results are robust for exposures to all natural disasters and those to only severe ones for educational and health outcomes. Interestingly, disaster exposure during the birth year and at age two shows persistent and significant effects on educational attainment for both women and men, whereas exposure at age one does not. While severe disaster exposure significantly reduces the likelihood of receiving any education, this effect is observed only among men. Individuals exposed to one additional severe disaster at age two are 1 percentage point less likely to have a long-term disease in their 20s and 30s, representing a 12.5% reduction compared to the average prevalence of long-term disease among women. Exposures to severe disasters after birth year significantly lower the probability of working with salary jobs for men.

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 the early-life exposure to natural disasters by years (ages). While in utero exposure to natural disasters has been found to have negative effects on later life, my results show that the following years can also be crucial, contributing to the literature on first 1,000 days or even longer period for early childhood development (Doyle 2020). 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), and my findings add new evidence that the adverse impacts can be long-lasting. 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 (1900-2023) (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).

1. A third wave is currently in the field.

2.3 Disaster Characteristics

The EM-DAT database records natural disasters as individual events. In the raw data provided as an Excel Worksheet, each row is one disaster event and columns are information associated with this one single event. One disaster has one unique disaster identifier generated by year, sequence number, and country ISO alpha 3 code. If one event affects several countries, it is recorded several times in the international database, but each event has one and unique identifier. The information of each disaster can be categorized into two groups: context variables and impact variables. Geographical and temporal information of each disaster are provided in context variables such as country name, ISO Code, region, continent, and river basin. Location of epicenter of earthquake is provided for earthquake. Admin level code and location names of all locations affected by each disaster are also listed, which are the crucial variables to use in this project to link individuals' location. Temporal information includes start date, end date, and local time. There is also physical characteristics such as origin, associated disasters 1 and 2, disaster magnitude scale and value. Aid contribution, OFDA response, appeal for international assistance and declaration are offered as disaster status. Impact variables can be used to assess the severity of each disaster. Health impact variables include number of deaths, missing persons, injuries, affected individuals, and those rendered homeless due to the disaster. Total estimated damages, reconstruction cost and insured losses are additionally included as economic impact information.

Although EM-DAT records disasters from 1900 to the present, in this study, I use only the events from 1970 to 2013 for the following reasons. First, individuals in my sample are interviewed in 2011-2013, and as the focus is on human capital outcomes in their 20s and 30s, the in utero year of eldest cohort goes back to 1970. Second, the farther back in time a natural disaster occurred, the more likely it is that information on the affected location is missing. Table 1 presents the availability of information on locations affected for disaster events over decades. For around one third of the disasters that happen before 1970, it is not observed which states or districts are affected by the events.

2.3.1 Link Disaster Events to District-Year

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.

To construct the district-cohort level disaster exposure, there are several steps. I first expand the list of location names, starting year, and ending year for each event, to create a disaster-location-year dataset, where the location can be either state or district. The goal is to build the disaster-district-year file based on districts in 2001 Census division as they are the geo-locations to link individuals in IHDS-II. However, the names of locations recorded for events in the EM-DAT raw file are the names used in the year when disaster occurs, and districts change names and/or boundaries over time, creating such a file requires manually constructing concordance between districts over time. There are some papers encoutering similar issues and share the dataset on location names over time (Kumar and Somanathan 2009; Sivadasan and Xu 2021; Dasgupta 2018). I build on the Indian District Equivalence Table shared by Dasgupta (2018) which contains the district name changes in 1951, 1961, 1971, 1981, 1991, and 2001. I combine this table with 2001 Census states and districts, 2011 Census states and districts, to create one linkage file from 1951 to 2011 of state names, one file for district names, and one file linking states and districts in 2001 Census division. With the linkage files, I extend the states affected by each disaster events into the districts affected in corresponding years, and link the disasters to 2001 Census districts. Out of 517 disaster events recorded in EM-DAT raw file in 1970-2013, I link 480 to districts in 2001 Census division. The summary statistics for these events will be discussed in Section 3.1.

2.3.2 Severity of Disaster Events

I use the measure, "number of people affected per 100 population", to define the severity of natural disaster events. This is a location-specific relative measure for disasters, compared to the absolute number of people affected or the number of deaths caused by disasters.

To calculate the population size of locations affected by each event, I use the India Census Population Table provided by Office of the Registrar General & Census Commissioner, India Ministry of Home Affairs (MHA), Government of India. Specifically, I use the Table "A-02: Decadal variation in population 1901-2011".[2] I extract census-year population for all districts and for the years that do not record population size, I linearly interpolate the population size at district-level to construct the population file for 2011 Census districts of every year from 1970. Merging it with the disaster-district-year file allows me to obtain the "human impact per capita" for each event. Another sensible measure for severity of disaster is the number of deaths over the population size residing in the area hit by disaster. I construct the measure, "number of deaths per 1 million population", and Figure A.1 presents the correlation between this measure and the measure used in the main analysis. The regressions using this measure to define severe disasters show similar results. In the main analysis, I take the disaster events affecting more 4 out of 100 people as the severe disasters.

2.4 Disaster Exposure Measures by District-Cohort

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. 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. 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

2. The India Census Population Table is from: https://censusindia.gov.in/census.website/data/census-tables. In Table A-02, there are tables for each states and within each table, the total population of the state and the population for each district within the state are included in years 1901, 1911, 1921, ..., 1991, 2001, 2011. In these years, female and male population are also offered.

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).

With the disaster-district-year file, I calculate for each district d in each year t number of disasters occurred, $ND_{dt,any}$, and number of severe disasters occurred, $ND_{dt,severe}$. Along with the interview year-month and birth year (or age) of individuals in IHDS, I generate a cohort-age level 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, $D^J_{dc,p\in\{any,severe\}}$, for cohort c in district d at age J, measuring if they have been exposed to type p disaster shock which considers either any disaster events or only severe disaster events. Furthermore, 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 early-life disaster exposure measure, $D_{dc,EarlyLife}$, which is the number of disaster events experienced in the period.

2.5 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, I include variables such as years of education completed, 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

As described in Section 2.1, 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.[3]

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).

3.1.1 Timing, Location and Severity of Disaster Events

In Table 2, 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.

Among the 480 events, floods (205 occurrences) and storms (117 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 280 deaths and affecting more than 4.8 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

3. 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.

most frequent phenomenon, with 117 events occurring between 1970 and 2013, 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 53 epidemics in India from 1970 to 2013. Most of these were caused by viral (24 events), bacterial (19 events), infectious disease (6 events), or parasitic (4 events) diseases. Taking a closer look at the event names, cholera is found to be the most frequent disaster in this category, 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). Extreme temperature events, including cold waves (23 events), heat waves (18 events), and severe winter conditions (1 event), were recorded 42 times from 1970 to 2013. This type of disaster 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 2 events are reported with associated disasters, such as drought, or rain/snow/ice.

Figure 2 illustrates the geographical variation in the number of all natural disasters across each district in India as recorded in EM-DAT. To capture temporal trends, the data is segmented into 10-year windows and each sub-figure presents one window. For districts not covered in my sample, I leave them blank in the maps. The number of disaster events overall increases over decades for the entire country. The northeastern area appears to be "disaster-prone area" in terms of all disasters. For example, Uttar Pradesh experienced the highest number of events from 2001 to 2010, with around 40 events.

3.1.2 Severe Disasters

Figure 4 is a histogram showing the distribution of all disaster events. Y axis presents the number of disaster events, and X axis is "number of people affected per 100 population". The disaster severity increases from left to right. The disaster events are separated into 1970-1989 group and

1990-2009 group according to the year of the events, hence two kinds of shape are used. It is readily observable that there are more disasters overall in the latter group, but if only the severe disasters are considered, which are those on the very right side of the figure, it is not always the case that disasters in 1990-2009 are more severe than those in 1970-1989. The vertical dashed line indicates the threshold I use to define severe disaster—disasters with top 20% high number of affected per 100 population. These are the events causing more than 4 out of 100 people homeless or injured beyond the deaths.

While Figure 2 presents the distribution of all disaster events, Figure 3 displays the geographical distribution of the severe disasters. I also aggregate the number of events by district and 10-year interval. There is still an increase in the number of events over time overall, but the "disaster-prone area" identified in Figure 2 are not prominently "shock-prone" under the case when only severe disasters are measured. States including West Bengal, Orissa, Andhra Pradesh, Kerala, Bihar, Gujarat, Uttar Pradesh, Haryana, and Punjab, are known as "India Flood Prone Areas" and experience frequent or severe flooding during the monsoon season, and some are also affected by cyclonic activities. This situation is reflected in the map, especially in years after 2000. Majority districts in states Gujarat, Maharashtra, Madhya Pradesh, Orissa have experienced 4 severe disasters in 2000-2009.

3.2 Individual Characteristics

The second wave of IHDS (IHDS-II) surveyed 204,560 individuals from 2011 to 2013 in the entire country. I restrict the sample to those whose households have been living in the same district since forever, which accounts for 86% of the all individuals. Then, my main sample contains the individuals who are 20 to 40 years old when they are interviewed, resulting in a sample of 59,066 individuals. I further construct early-life exposures to natural disasters by cohort and district, and human capital outcomes for each individuals, as detailed in Section 2.5.

3.2.1 Sample Overview

An overview of the sample composition and human capital variables clustered by gender is presented in Table 3. Within the total sample comprising 59,066 individuals, 51% are female. The average age is 29 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, 78% of individuals have received some education, and around 7 years of education is completed on average for all individuals. The share of men receiving any kind of education is higher than women, and they on average obtain 2 more years of education than women. Across all three educational measures—share of individuals with any education, share completing lower primary school, and share completing upper primary school—women's rates are consistently 17 percentage points lower than men's. For instance, only half of women complete upper primary school, compared to 70% of men. In terms of health status, women are "weaker" compared to men. 8% of women have or have had long-term disease at some point in their life, regardless of recovery status, compared to 5% of men. Also, the share of women with short-term sickness is nearly double that of men. In the whole sample, over 60% participate in some form of work, but only about 13% are employed in monthly or annual salaried positions. A substantial gender gap exists in labor participation: fewer than half of women work, compared to 87% of men; Only 8% of women work full-time, compared to 43% of men.

Table 4 provides summary statistics on early-life disaster exposures by gender. For each gender, it presents the total number of disasters experienced during early life, along with breakdowns for specific periods: in utero, birth year, age one, and age two. The number of severe disaster events is also presented in this format. Notably, the total count of early-life disaster exposures is the sum across these years. Individuals experienced up to a maximum of 12 disaster events in early life, with exposure in each developmental stage reaching as high as five events. On average, individuals faced more than two disaster events in early life. Even when focusing solely on severe disasters, individuals encountered, on average, over one severe event per year during early life, with a maximum exposure of four severe events across this period.

3.2.2 Human Capital and Disaster Exposures

I furthermore provide illustrative evidence on disaster exposures and human capital outcomes using the trends of outcomes over ages. Figures 5, 6, and A.2 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 5, 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 educational attainment. Within each gender, those exposed to natural disaster shocks in early life have a lower educational attainment ratio compared to their non-exposed counterparts. In Figure 6, 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 A.2 focuses on labor force participation specifically for jobs with monthly or annual salaries. As a result, the ratio is considerably lower compared to Figure 6. 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 early-life natural disaster exposure by years during this 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 $\{$*in utero, birth year, age 1, age 2*$\}$; 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.

As the district of birth is not directly observed in IHDS, I assume that individual's district of residence when surveyed is the location of birth using several piece of information and restrict my sample. IHDS-II asks 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.[4] I accordingly drop the individuals whose households have moved across districts, as the chance of them being born in the current districts is much lower. 68,421 individuals who are aged 20 to 40 are surveyed in IHDS-II, and my main sample includes 87% of them. Additionally, at individual level, IHDS-II asks about migration history in recent 5 years related to seasonal or short-term work. Out of 68,421 individuals aged 20 to 40 in IHDS-II, 97% have not migrated for seasonal or short-term work.[5] I did not drop observations based on this information, as this does not relate to the decision on taking district of residence as district of birth.

5 Results

5.1 Early-life Natural Disaster Exposure and Adulthood Human Capital

To examine the effects on human capital, Equation 4.1 is estimated using a linear probability model. I focus on three sets of outcomes, educational and health outcomes, and labor force participation, which I discuss sequentially.

Table 6 and Table 8 show results for the effects of number of any disasters exposed in early life, while Table 5 and Table 7 show results for the effects of number of only severe disasters. Each table contains several panels, with results for the entire sample (all individuals) with gender fixed

4. 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.

5. 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". If yes, then the place of migration is recorded in these categories: "same state", "another state", "abroad".

effects, results for women only, and results for men only. For labor market outcomes, there is no panel for all individuals, as the labor market is systematically different for women and men in India, it is appropriate to directly look at the outcomes for them separately.

5.1.1 Education and Health

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. The regressions in all columns control for age, caste and religion, while incorporating district fixed effects and cohort fixed effects, and interview year and month fixed effects, to control variations across cohorts within districts.

Severe disasters. In Table 5, column (2) shows that for the people exposed to one more severe disaster event in early life, they receive 0.147 fewer years, i.e. 1.8 month of education. This does not seem too bad as the average years of education for all individuals is 7.27. However, considering the people exposed to most severe disasters which is 4 events exposure in early life, they can lose about 0.6 years, i.e. 7 months of education, compared to those who are not exposed to severe disasters. This loss of education accounts for 8% of the average years of education. This effects are strong and persistent across gender. Women who are exposed to 4 severe disaster events have 8.6% fewer years of education compared to those not exposed. For men, being exposed to one more severe disaster event means loss of almost 2 months of education. Column (3) and (4) show that the probability of completing primary school is low for both gender if they are exposed to severe disasters in early-life. On average, being exposed to one additional severe disaster lowers the probability of completing upper primary school by 1.1 percentage point.

In terms of health outcomes, the probability of having or having had a long-term disease is not affected by early-life exposure if any disaster is considered (Table 6, column (5) and (6)). However, surprisingly, Table 5 show that women exposed to one more severe disaster event in early life face a 0.6 percentage point lower probability of having long-term disease. The share of women with long-term disease is 8%, meaning that women being exposed to one more event have 7.5%

lower chance of having long-term disease in their 20 to 40 age period. As this difference does not appear for men, one hypothesis is that there is gender-specific survival bias. I only observe adults who survive and make it into the sample restricted to population aged 20 to 40. If disaster exposure increases mortality, it could affect the composition of the sample. If the mortality effect of disaster exposure is homogeneous across women and men, then the results should be consistent for both groups. However, if the mortality rate is higher for women exposed to severe disasters compared to women not exposed or less exposed, and women with long-term disease are likely to have even higher mortality rate, then women exposed to more early-life severe disasters in early life and surviving after age 20 are healthier than women exposed to fewer early-life severe disasters.

Any disasters. The results for considering all disaster are quite different. In this setting, I consider the fact that certain area is disaster-prone, the possibility that districts can be well-prepared for and households are adapted to non-severe disasters. By looking at any disasters, individuals who are in "control" group when considering the exposure to severe disasters are switched to "treatment" group, as those who have not been exposed to severe disasters are categorized to be exposed to disaster events. When considering all disasters recorded in EM-DAT (Table 6), all individuals aged 20 to 40 who are exposed to one more natural disaster during early life show, on average, a weak 0.2 percentage point reduction in the probability of having received any education. Women are found to be 16.5 percentage points less likely to have received an education compared to men, and across all columns for educational outcomes, women are worse off than men. However, women are overall more likely to have or have had long-term disease and being sick in the last 30 days (short-term sickness). When clustering the sample by gender, results show that within women, being exposed to more disasters does not affect these outcomes, but there is a 0.3 percentage point reduction in the probability of having received any education for men.

5.1.2 Labor Force Participation

Table 7 presents results when only severe disaster events are considered for early-life exposure on labor force participation, and the sample is clustered by gender for the estimation as the gap between women and men is systematically large. Table 8 presents results for effects of exposure to number of any disasters. There are four binary variables included: working for any job, being a salary worker paid monthly or annually, working full-time for any job, working full-time for salary paid monthly or annually.

Severe disasters. Table 7 shows the results estimating effects of only severe disasters. Women exposed to one more disaster event show 1.3 percentage point rise in the probability of working for any job. If having long-term disease or not is a feasible measure for health status, it is possible that this population is physically stronger and more likely to participate in activities in general. Men are particularly worse off if they have been exposed to severe disasters in early life. Column (4) indicates that being exposed to one more severe disaster lowers the probability of working full-time for a salary position by 1.2 percentage point, which is 7.5% decrease for men.

Any disasters. When considering all disasters recorded in EM-DAT (Table 8), men aged 20 to 40 who experienced one more natural disaster during early life show, on average, a 0.5 percentage point reduction in the probability of working for any type of jobs. The jobs include family-own farm, family-business, and salary jobs. Compared to the share of men working for any job (87% in Table 3), the magnitude of effect is as small as 0.5%.

5.2 Effects of Year-by-Year Exposure in Early Life

The findings in Table 5 demonstrate that early-life exposure to severe disasters 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. In the context of a country with son preference, girls estimating if the events occurring post-utero have substantial impacts on adult outcomes is meaningful. This may serve as the first step to delve deeper into the mechanism of why there is gender-differed effects of a non-gender-differed exogenous negative shocks in early life on human capital in the long run.

To address this, Equation 4.2 is estimated and this section discusses results on disaster exposure by years in early-life period and human capital outcomes detailed in Table A.2, Table A.3, Table A.4, and Table A.5. Panels in each tables are for different population in the sample, with observations are omitted for brevity. Rather than aggregating the number of disaster exposed to in the entire period, in Equation 4.2 disaster shock variables include the number of disasters exposed in utero, in bith year, in the year after birth year (age 1), and in the year after that year (age 2). Since I do not observe the birth month, the year "in utero" does not necessarily mean the individuals are in utero if they are born after September, so this measure of disaster exposure at each age will be somewhat noisy. As long as it is not systematically biased, this will only attenuate results.

5.2.1 Education and Health

Looking at exposure to only severe disasters, Table A.2 shows consistent results in terms of exposures in utero in all panels. Interestingly, exposure in birth year and the age 2 year show persistent significantly effects on educational attainments for both women and men, but not the exposure in age 1 year. While the exposure to severe disasters show significant negative effects on the likelihood of receiving any education, the effects only appear for men. Being exposed to one more severe disasters in birth year and age 2 indicates 1.5 and 1.2 percentage points reduction in the probability of receiving any education, respectively. The summary statistics Table 4 shows that one person could have been exposed to two severe disasters in these one-year period. This means for the population exposed to most severe disasters, the probability is 5.4 percentage points lower than those who are not exposed to severe disasters in any of the years, accounting for more than 6% of the average share of people receiving education. Yet the effects in terms of years of education completed are consistently negative and the magnitude is not small. For women, being exposed to one additional severe disaster event in birth year and in age 2 indicate 0.134 and 0.175 fewer year of education, respectively. The summary statistics Table 4 shows that one person could have been exposed to two severe disasters in these one-year period, which means for the population exposed to most severe disasters, 0.62 years of education can be lost due to the disaster shocks, which is around 10% reduction of the average years of education for women. The effect on years of education is also significant for men. Being exposed to severe disasters in birth year and age 2 together can reduce more than half year of education. Again, for the men exposed to most disasters, this accounts for losing 12.7% years of education.

The health effects of early-life exposure to severe disasters only appear for women. Those exposed to one more severe disaster in age 2 are less likely to have long-term disease in their 20s and 30s by 1 percentage point equivalent to 12.5% reduction compared to average share of women with long-term disease. Having short-term disease, defined as "being sick in the last 30 days (fever, cough, and diarrhea)", can be related to many other factors. But if this is also taken as an indicator of physical status at the time of survey, it may echo the effects found for long-term disease. Interestingly, column (6) shows that being exposed to one more severe disaster in birth year leads to 1.4 percentage point (8.8%) decrease in the probability of having short-term sickness.

Shown in Table A.3, exposures in utero considering all kinds of disasters appear to be weakly or not associated with the likelihood of receiving education, years of education, probability of completing primary school, having long-term, and having short-term sickness. Conversely, exposures in birth year and years afterwards lower the educational attainment. For women, being exposed to one more disaster of any kind in the birth year significantly lowers the probability of being educated and completing low primary school by approximately 0.9 percentage point, a pattern also shown for exposure in the age 2 year.

5.2.2 Labor Force Participation

The results presented in Table A.4 and Table A.5 stem from regressions based on Equation 4.2, separately conducted for males and females to examine labor force participation in either any kind of job or formal jobs with salary. Table A.4 shows that exposure to severe disasters after birth significantly affects the probability of labor force participation for both genders, with an increase of more than 1.3 percentage point for women but a decrease of around 2 percentage point for men, while results from considering all disasters recorded in EM-DAT database show no or weak effects in Table A.5.

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 adulthood (age 20 to 40). To do so, all disasters occurring from 1970 to 2013 in India are matched to district-year. One natural disaster is identified as severe event if it has affected more than 4 people per 100 population residing in the areas hit by this event. Then, for birth cohorts in each district, I construct the number of disaster events experienced in utero, birth year, age 1 year, and age 2 year, which is further summed up to measure the early-life disaster exposure. The early-life exposure to severe events is constructed following the same process. Linking the disaster exposure with individuals interviewed in the second wave of the Indian Human Development Survey (IHDS-II), I estimate the long-term effects of early-life exposure to natural disasters considering the frequency and severity of disaster events. 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 results reveal that, on average, early-life exposures to severe natural disasters significantly decrease the probability of ever being educated, years of education, and probability of completing primary school, for both women and men. Women who are exposed to severe events in early-life show lower incidence of having long-term disease, which indicates gender-differentiated survival bias. The early-life exposures reduce labor force participation in both general work and jobs paid monthly or annually for men but not women. 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 exposures to severe disasters in early-life shows that natural disasters occurring during the birth year and the subsequent year (ages 1 to 2) affect the educational and health outcomes in adulthood. However, weak or no corresponding effects are observed for in utero and birth-year exposures on labor force participation. Only exposures in the following years significantly lowers the probability of working for salary jobs.

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: Summary statistics of all disasters in India from EM-DAT

Year	Event No.	Share of Events with Location Info	Avg. Deaths	Avg. Affected
1900-1909	3	66.67%	856,667	NA
1910-1919	1	100.00%	300	NA
1920-1929	10	60.00%	358,338	347,337
1930-1939	3	66.67%	20,111	NA
1940-1949	8	100.00%	257,801	16,000
1950-1959	28	50.00%	277	229,565
1960-1969	41	63.41%	44,649	5,877,478
1970-1979	58	93.10%	767	9,820,981
1980-1989	107	90.65%	314	10,783,917
1990-1999	115	99.13%	465	4,039,702
2000-2009	184	100%	357	4,626,611
2010-2019	162	100.00%	143	4,417,043

Note: This table shows summary statistics for all disasters from EM-DAT database, including number of disaster events, availability of information on locations affected affected by disaster events, number of deaths, and number of people affected by disaster events. EM-DAT records the disasters by events, and for each event, a list of location names should be provided, but the availability of this piece of information varies. Since 1970, the availability increases significantly. For example, among 58 natural disasters happened in 1970-1979, for 6.9% events it is not observed which areas are affected. These events will not be merged with specific districts or individuals, and tend to have less impacts on human activity.

Table 2: Natural disaster characteristics

Disasters	# of Events	1st quartile	Mean	3st quartile	SD	CV	Skewness	Kurtosis
Flood	205							
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	117							
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	53							
Death		46	298	296	578	2	4	15
Affected		205	11,095	5,642	28,942	3	4	16
Damage								
Extreme temperature	42							
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)	35							
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	16							
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	8							
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	2							
Death		6	6	6				
Affected								
Damage		5,866	5,866	5,866				
Mass movement (dry)	1							
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. Of the 517 disaster events 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, 8 droughts, 2 wildfires, 1 mass movement (dry), and 1 infestation. No data on death, affected, or damage are recorded for the infestation event.

Table 3: Sample overview by gender

	Women				
	Mean	SD	Min	Max	N
Age	29.25	6.26	20	40	30,304
Interview year	2011.88	0.32	2011	2012	30,304
Interview month	5.75	2.99	1	12	30,304
Birth year	1982.63	6.26	1971	1992	30,304
Hindu upper caste	0.20	0.40	0	1	30,298
Hindu marginalized caste	0.64	0.48	0	1	30,298
Muslim	0.14	0.35	0	1	30,298
Ever attended school	0.70	0.46	0	1	30,274
Years of education (never=0)	6.36	5.10	0	15	30,273
Lower primary school completed	0.64	0.48	0	1	30,273
Upper primary school completed	0.53	0.50	0	1	30,273
Have or had long-term disease	0.08	0.27	0	1	30,304
Sick in last mo. (diarrhea, fever, cough)	0.16	0.36	0	1	30,304
Worker with any job	0.47	0.50	0	1	30,304
Salary worker paid monthly or annually	0.06	0.24	0	1	30,304
Full-time worker with any job	0.08	0.26	0	1	30,304
Full-time salary worker paid monthly or annually	0.03	0.18	0	1	30,304
	Men				
	Mean	SD	Min	Max	N
Age	29.26	6.22	20	40	28,762
Interview year	2011.89	0.32	2011	2012	28,762
Interview month	5.78	2.96	1	12	28,762
Birth year	1982.63	6.23	1971	1992	28,762
Hindu upper caste	0.20	0.40	0	1	28,755
Hindu marginalized caste	0.64	0.48	0	1	28,755
Muslim	0.14	0.35	0	1	28,755
Ever attended school	0.87	0.34	0	1	28,715
Years of education (never=0)	8.23	4.56	0	15	28,704
Lower primary school completed	0.80	0.40	0	1	28,704
Upper primary school completed	0.70	0.46	0	1	28,704
Have or had long-term disease	0.05	0.21	0	1	28,762
Sick in last mo. (diarrhea, fever, cough)	0.09	0.29	0	1	28,762
Worker with any job	0.87	0.33	0	1	28,762
Salary worker paid monthly or annually	0.21	0.40	0	1	28,762
Full-time worker with any job	0.43	0.50	0	1	28,762
Full-time salary worker paid monthly or annually	0.16	0.37	0	1	28,762

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

Table 4: Summary statistics for disaster exposure

	Women				
	Mean	SD	Min	Max	N
No. of any disasters					
Early-life	2.57	2.37	0	12	30,304
In utero	0.59	0.91	0	5	30,304
Birth year	0.60	0.88	0	5	30,304
Age 1	0.68	0.93	0	5	30,304
Age 2	0.69	0.88	0	5	30,304
No. of severe disasters					
Early-life	0.51	0.73	0	4	30,304
In utero	0.11	0.32	0	2	30,304
Birth year	0.13	0.34	0	2	30,304
Age 1	0.13	0.34	0	2	30,304
Age 2	0.14	0.35	0	2	30,304
	Men				
	Mean	SD	Min	Max	N
No. of any disasters					
Early-life	2.54	2.36	0	12	28,762
In utero	0.59	0.90	0	5	28,762
Birth year	0.61	0.89	0	5	28,762
Age 1	0.66	0.90	0	5	28,762
Age 2	0.69	0.88	0	5	28,762
No. of severe disasters					
Early-life	0.51	0.75	0	4	28,762
In utero	0.11	0.32	0	2	28,762
Birth year	0.13	0.34	0	2	28,762
Age 1	0.13	0.34	0	2	28,762
Age 2	0.14	0.35	0	2	28,762

Note: This table displays an overview for early-life disaster exposures for the sample constructed from IHDS-II dataset. For each individual, the number of natural disaster events experienced during key early-life periods—in utero, the birth year, the year following birth (age 1), and the subsequent year (age 2)—is calculated. The total number of events across these periods is summed to represent early-life disaster exposure. Two types of disaster events are analyzed: (1) any disasters recorded in EM-DAT and (2) severe disasters, defined as those affecting more than four individuals per 100 population.

Table 5: Effects of severe disasters on education and health

	(1) Ever educated	(2) Years of education	(3) Complete low primary sch	(4) Complete upper primary sch	(5) Long-term disease	(6) Short-term sickness
			All individuals			
Early-life shock	-0.003	-0.147***	-0.007*	-0.009**	-0.003**	-0.003
	(0.003)	(0.040)	(0.004)	(0.004)	(0.001)	(0.002)
Female	-0.165***	-1.887***	-0.165***	-0.171***	0.035***	0.068***
	(0.007)	(0.074)	(0.007)	(0.007)	(0.003)	(0.004)
Observations	58976	58964	58964	58964	59053	59053
			Women			
Early-life shock	-0.001	-0.137***	-0.005	-0.011**	-0.006**	-0.006
	(0.005)	(0.044)	(0.004)	(0.005)	(0.002)	(0.004)
Observations	30268	30267	30267	30267	30298	30298
			Men			
Early-life shock	-0.006*	-0.163***	-0.010**	-0.007	-0.001	-0.001
	(0.004)	(0.055)	(0.005)	(0.006)	(0.002)	(0.003)
Observations	28708	28697	28697	28697	28755	28755
Age	Y	Y	Y	Y	Y	Y
Caste and religion	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Interview yr FE	Y	Y	Y	Y	Y	Y
Interview mo FE	Y	Y	Y	Y	Y	Y
Cohort FE	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. The early-life disaster exposure measure is the number of disasters experienced from in utero to age two. “Severe disasters” means that only severe events are considered, and one disaster is defined as severe event if it causes more than four people affected (injured or homeless) per 100 population. Age range: [20, 40].

Table 6: Effects of any disasters on education and health

	(1) Ever educated	(2) Years of education	(3) Complete low primary sch	(4) Complete upper primary sch	(5) Long-term disease	(6) Short-term sickness
			All individuals			
Early-life shock	-0.002*	-0.009	-0.002	-0.001	0.001	-0.000
	(0.001)	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)
Female	-0.165***	-1.886***	-0.165***	-0.171***	0.035***	0.068***
	(0.007)	(0.074)	(0.007)	(0.007)	(0.003)	(0.004)
Observations	58976	58964	58964	58964	59053	59053
			Women			
Early-life shock	-0.002	-0.007	-0.002	-0.002	0.000	-0.001
	(0.002)	(0.019)	(0.002)	(0.002)	(0.001)	(0.002)
Observations	30268	30267	30267	30267	30298	30298
			Men			
Early-life shock	-0.003*	-0.007	-0.002	0.000	0.000	0.001
	(0.001)	(0.021)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	28708	28697	28697	28697	28755	28755
Age	Y	Y	Y	Y	Y	Y
Caste and religion	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Interview yr FE	Y	Y	Y	Y	Y	Y
Interview mo FE	Y	Y	Y	Y	Y	Y
Cohort FE	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. The early-life disaster exposure measure is the number of disasters experienced from in utero to age two. "Any disasters" means that all events recorded in EM-DAT are considered. Age range: [20, 40].

Table 7: Effects of severe disasters on labor force participation

	(1) Worker with any job	(2) Salary worker	(3) Full-time worker with any job	(4) Full-time salary worker
		Women		
Early-life shock	0.013***	0.002	0.004	-0.001
	(0.005)	(0.002)	(0.002)	(0.002)
Mean	0.47	0.06	0.08	0.03
Observations	30298	30298	30298	30298
		Men		
Early-life shock	0.001	-0.013**	-0.006	-0.012***
	(0.004)	(0.005)	(0.005)	(0.005)
Mean	0.87	0.21	0.43	0.16
Observations	28755	28755	28755	28755
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
Cohort FE	Y	Y	Y	Y

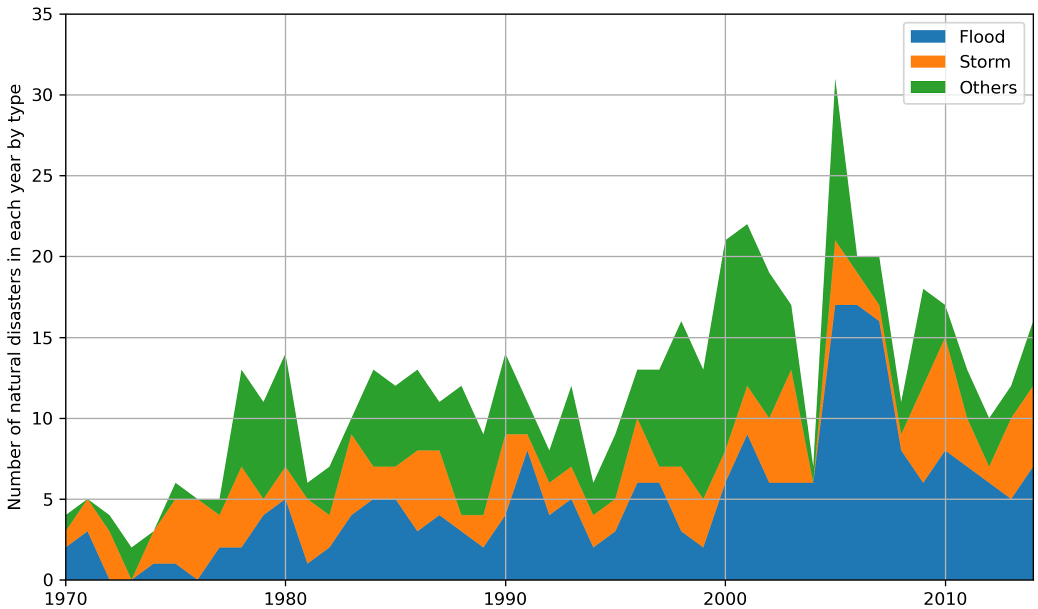
Note: This table shows regression results corresponding to Equation 4.1. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. The early-life disaster exposure measure is the number of disasters experienced from in utero to age two. "Severe disasters" means that only severe events are considered, and one disaster is defined as severe event if it causes more than four people affected (injured or homeless) per 100 population. Age range: [20, 40].

Table 8: Effects of any disasters on labor force participation

	(1) Worker with any job	(2) Salary worker	(3) Full-time worker with any job	(4) Full-time salary worker
		Women		
Early-life shock	-0.001	0.001	-0.001	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Mean	0.47	0.06	0.08	0.03
Observations	30298	30298	30298	30298
		Men		
Early-life shock	-0.005***	-0.000	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Mean	0.87	0.21	0.43	0.16
Observations	28755	28755	28755	28755
Age	Y	Y	Y	Y
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
Cohort FE	Y	Y	Y	Y

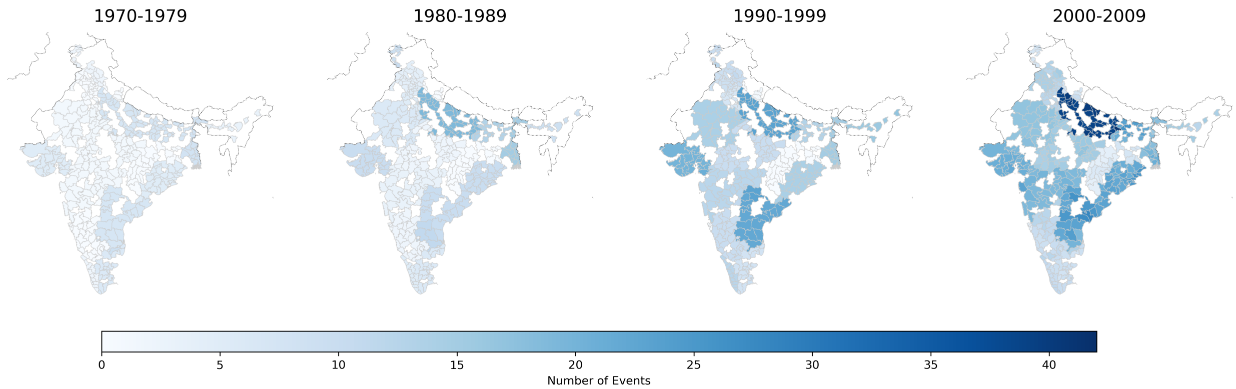
Note: This table shows regression results corresponding to Equation 4.1. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. The early-life disaster exposure measure is the number of disasters experienced from in utero to age two. “Any disasters” means that all events recorded in EM-DAT are considered. Age range: [20, 40].

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



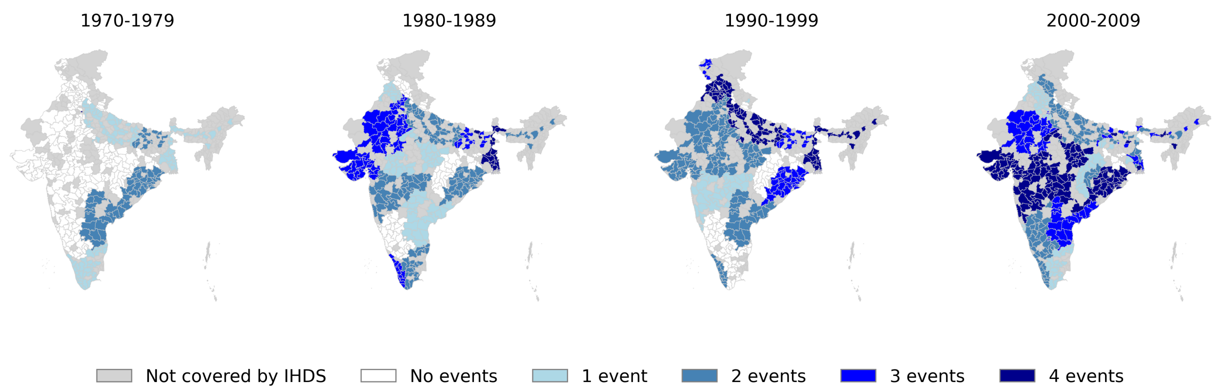
Note: This considers all natural disasters recorded in EM-DAT data in India from 1970 to 2014.

Fig. 2. Number of all disasters experienced by districts in 10-year intervals



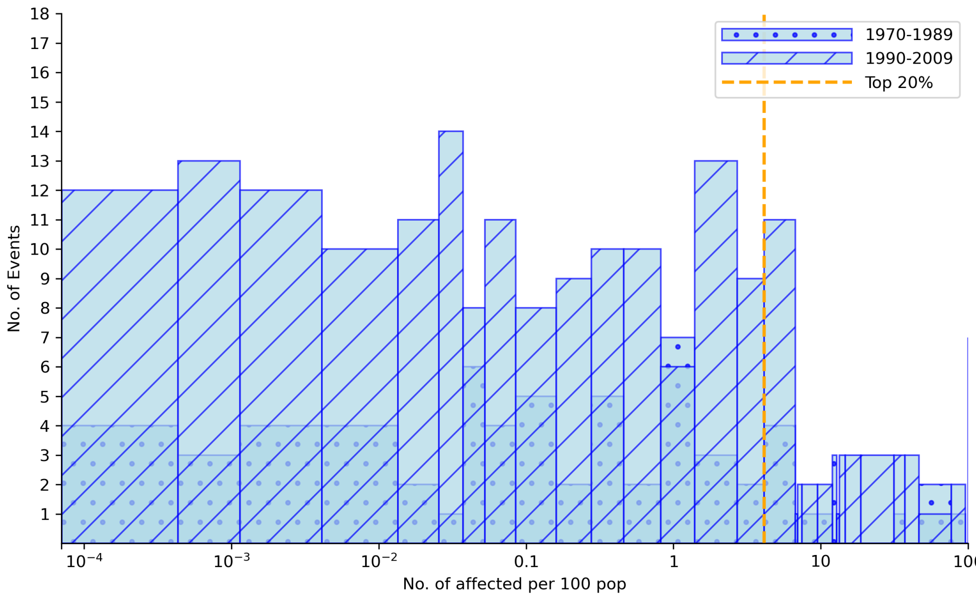
Note: This shows the geographical variation in the number of all natural disasters across each district in India as recorded in EM-DAT. To capture temporal trends, the data is segmented into 10-year windows and each sub-figure presents one window. Districts not covered in my sample are left blank.

Fig. 3. Number of severe disasters experienced by districts in 10-year intervals



Note: This displays the geographical distribution of the severe disasters. The number of severe events by district is aggregated in 10-year interval and each sub-figure presents one decade. Districts not covered in my sample are in gray. The early-life disaster exposure measure is the number of disasters experienced from in utero to age two. "Severe disasters" means that only severe events are considered, and one disaster is defined as severe event if it causes more than four people affected (injured or homeless) per 100 population.

Fig. 4. Number of years in natural disaster shocks by districts in 2001-2010

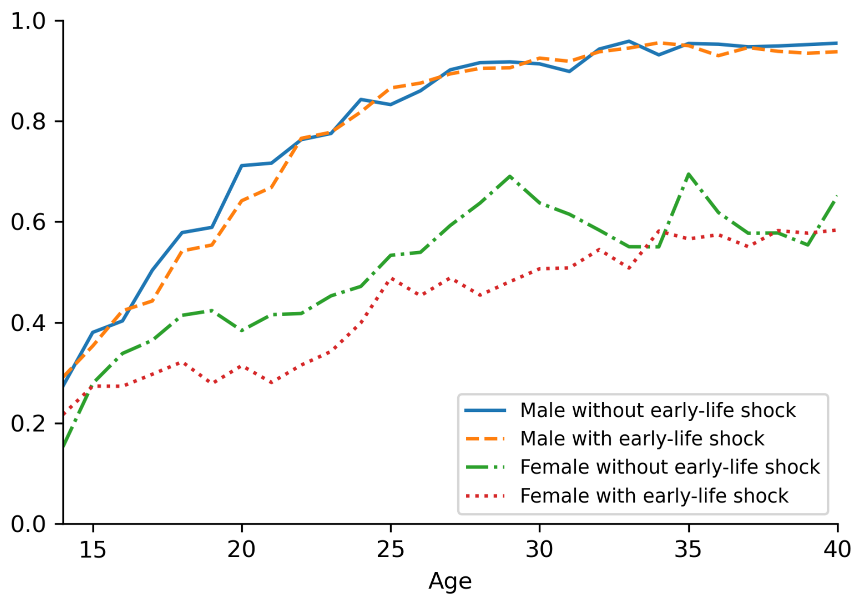


Note: This presents a histogram showing the distribution of all disaster events. Y axis presents the number of disaster events, and X axis is "number of people affected per 100 population". The disaster severity increases from left to right. The disaster events are separated into 1970-1989 group and 1990-2009 group according to the year of the events, shown with two kinds of shape. The vertical dashed line indicates the threshold I use to define severe disaster—disasters with top 20% high number of affected per 100 population. These are the events affecting more than four out of 100 population.

Fig. 5. Share of people ever educated over ages

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. 6. Share of people working for any job over ages



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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ONLINE APPENDIX

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

Yujie Zhang

A Appendix Figures and Table (Online)

Table A.1: Sample overview

	Mean	SD	Min	Max	N
Female	0.51	0.50	0	1	59,066
Age	29.26	6.24	20	40	59,066
Interview year	2011.88	0.32	2011	2012	59,066
Interview month	5.77	2.98	1	12	59,066
Birth year	1982.63	6.25	1971	1992	59,066
Caste/religion					
Hindu upper caste	0.20	0.40	0	1	59,053
Hindu marginalized caste	0.64	0.48	0	1	59,053
Muslim	0.14	0.35	0	1	59,053
Other caste/religion	0.02	0.15	0	1	59,053
Outcome: Education					
Ever attended school	0.78	0.41	0	1	58,989
Years of education (never=0)	7.27	4.93	0	15	58,977
Lower primary school completed	0.72	0.45	0	1	58,977
Upper primary school completed	0.61	0.49	0	1	58,977
Outcome: Health					
Have or had long-term disease	0.06	0.25	0	1	59,066
Sick in last mo. (diarrhea, fever, cough)	0.12	0.33	0	1	59,066
Outcome: Labor					
Worker with any job	0.67	0.47	0	1	59,066
Salary worker paid monthly or annually	0.13	0.34	0	1	59,066
Full-time worker with any job	0.25	0.43	0	1	59,066
Full-time salary worker paid monthly or annually	0.09	0.29	0	1	59,066

Note: This table displays an overview for sample constructed from IHDS-II dataset, restricted to individuals whose households have been living in the same district always.

Table A.2: Effects of severe disasters in early-life years on education and health

	(1) Ever educated	(2) Years of education	(3) Complete low primary sch	(4) Complete upper primary sch	(5) Long-term disease	(6) Short-term sickness
			All individuals			
In utero	0.004	-0.046	0.001	-0.002	-0.006*	-0.002
	(0.006)	(0.081)	(0.007)	(0.008)	(0.003)	(0.005)
Birth year	-0.014**	-0.209***	-0.010	-0.011*	0.001	-0.007
	(0.006)	(0.060)	(0.006)	(0.007)	(0.003)	(0.004)
Age 1	0.003	-0.114	-0.009	-0.008	-0.004	0.003
	(0.006)	(0.073)	(0.007)	(0.008)	(0.003)	(0.005)
Age 2	-0.005	-0.195***	-0.009*	-0.014**	-0.005	-0.006
	(0.005)	(0.061)	(0.006)	(0.006)	(0.003)	(0.004)
			Women			
In utero	0.003	-0.102	0.003	-0.005	-0.009*	-0.008
	(0.009)	(0.094)	(0.009)	(0.009)	(0.005)	(0.007)
Birth year	-0.013	-0.134*	-0.011	-0.015*	-0.001	-0.014**
	(0.008)	(0.076)	(0.008)	(0.008)	(0.005)	(0.007)
Age 1	0.006	-0.130	-0.005	-0.010	-0.004	0.007
	(0.008)	(0.088)	(0.009)	(0.009)	(0.005)	(0.007)
Age 2	0.000	-0.175**	-0.003	-0.015*	-0.010**	-0.009
	(0.008)	(0.086)	(0.008)	(0.008)	(0.005)	(0.007)
			Men			
In utero	0.005	0.022	0.000	0.001	-0.002	0.005
	(0.007)	(0.110)	(0.010)	(0.011)	(0.004)	(0.007)
Birth year	-0.015**	-0.291***	-0.008	-0.007	0.003	0.001
	(0.007)	(0.087)	(0.008)	(0.010)	(0.004)	(0.005)
Age 1	-0.000	-0.109	-0.014	-0.006	-0.003	-0.001
	(0.008)	(0.106)	(0.009)	(0.010)	(0.003)	(0.006)
Age 2	-0.012**	-0.230***	-0.017**	-0.016*	-0.002	-0.006
	(0.006)	(0.079)	(0.007)	(0.009)	(0.004)	(0.005)
Age	Y	Y	Y	Y	Y	Y
Caste and religion	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Interview yr FE	Y	Y	Y	Y	Y	Y
Interview mo FE	Y	Y	Y	Y	Y	Y
Cohort FE	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. The early-life disaster exposure measure is the number of disasters experienced from in utero to age two. "Severe disasters" means that only severe events are considered, and one disaster is defined as severe event if it causes more than four people affected (injured or homeless) per 100 population. Age range: [20, 40].

Table A.3: Effects of any disasters in early-life years on education and health

	(1) Ever educated	(2) Years of education	(3) Complete low primary sch	(4) Complete upper primary sch	(5) Long-term disease	(6) Short-term sickness
			All individuals			
In utero	0.002	0.034	0.003	0.002	-0.001	0.004*
	(0.002)	(0.027)	(0.003)	(0.003)	(0.001)	(0.002)
Birth year	-0.006**	-0.046*	-0.004	-0.002	0.001	-0.002
	(0.002)	(0.026)	(0.003)	(0.003)	(0.002)	(0.002)
Age 1	-0.000	0.002	-0.002	-0.002	0.001	-0.001
	(0.002)	(0.025)	(0.002)	(0.003)	(0.001)	(0.002)
Age 2	-0.004*	-0.016	-0.004	-0.003	0.000	-0.000
	(0.002)	(0.030)	(0.003)	(0.003)	(0.002)	(0.002)
			Women			
In utero	0.005	0.033	0.007*	0.002	-0.001	0.005
	(0.004)	(0.039)	(0.004)	(0.004)	(0.002)	(0.003)
Birth year	-0.009**	-0.052	-0.009**	-0.004	0.000	-0.004
	(0.004)	(0.036)	(0.004)	(0.004)	(0.002)	(0.003)
Age 1	0.003	0.039	0.003	-0.001	0.003	-0.002
	(0.003)	(0.034)	(0.003)	(0.004)	(0.002)	(0.003)
Age 2	-0.007*	-0.049	-0.008**	-0.005	-0.001	-0.001
	(0.004)	(0.039)	(0.004)	(0.004)	(0.002)	(0.003)
			Men			
In utero	-0.002	0.041	-0.001	0.002	-0.000	0.004
	(0.003)	(0.038)	(0.004)	(0.004)	(0.002)	(0.003)
Birth year	-0.003	-0.038	0.002	0.002	0.002	-0.000
	(0.003)	(0.035)	(0.003)	(0.004)	(0.002)	(0.002)
Age 1	-0.003	-0.033	-0.007**	-0.003	-0.002	0.000
	(0.003)	(0.040)	(0.004)	(0.004)	(0.002)	(0.002)
Age 2	-0.002	0.019	-0.001	0.000	0.001	-0.001
	(0.003)	(0.038)	(0.003)	(0.004)	(0.002)	(0.003)
Age	Y	Y	Y	Y	Y	Y
Caste and religion	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Interview yr FE	Y	Y	Y	Y	Y	Y
Interview mo FE	Y	Y	Y	Y	Y	Y
Cohort FE	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. The early-life disaster exposure measure is the number of disasters experienced from in utero to age two. "Any disasters" means that all events recorded in EM-DAT are considered. Age range: [20, 40].

Table A.4: Effects of severe disasters in early-life years on labor force participation

	(1) Worker with any job	(2) Salary worker	(3) Full-time worker with any job	(4) Full-time salary worker
	Women			
In utero	0.009	0.003	-0.002	-0.004
	(0.011)	(0.004)	(0.006)	(0.003)
Birth year	0.014	0.000	0.000	-0.003
	(0.009)	(0.004)	(0.005)	(0.003)
Age 1	0.011	0.005	0.013***	0.005
	(0.009)	(0.004)	(0.005)	(0.004)
Age 2	0.017**	-0.000	0.002	-0.002
	(0.008)	(0.005)	(0.005)	(0.004)
	Men			
In utero	-0.001	-0.016*	-0.011	-0.009
	(0.009)	(0.009)	(0.010)	(0.008)
Birth year	-0.002	-0.009	-0.005	-0.009
	(0.007)	(0.009)	(0.010)	(0.008)
Age 1	0.011	-0.002	0.012	-0.011
	(0.008)	(0.008)	(0.010)	(0.007)
Age 2	-0.005	-0.025***	-0.019*	-0.019**
	(0.008)	(0.008)	(0.010)	(0.008)
Age	Y	Y	Y	Y
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
Cohort FE	Y	Y	Y	Y

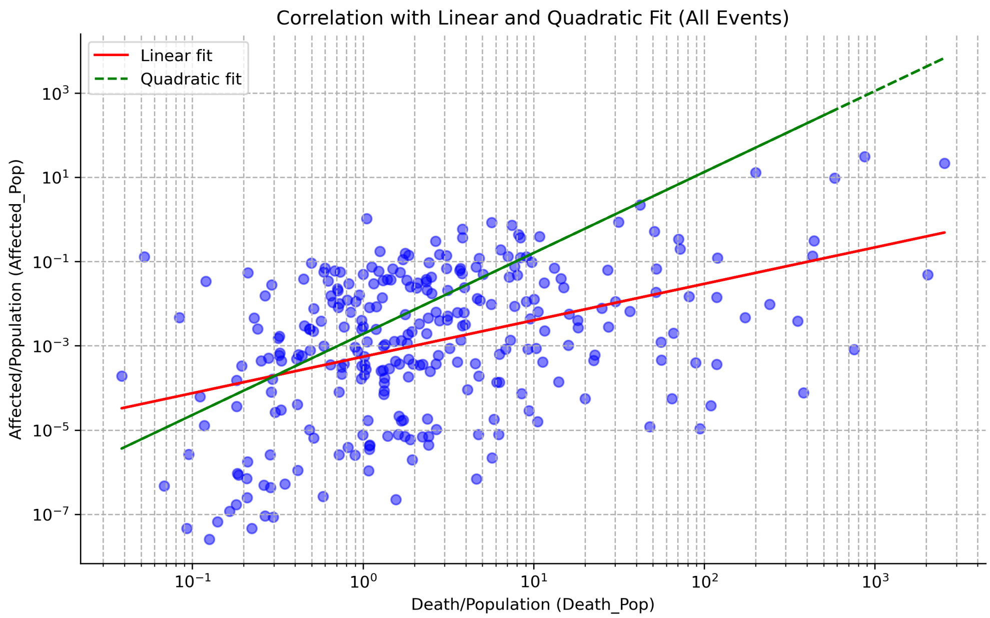
Note: This table shows regression results corresponding to Equation 4.1. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. The early-life disaster exposure measure is the number of disasters experienced from in utero to age two. "Severe disasters" means that only severe events are considered, and one disaster is defined as severe event if it causes more than four people affected (injured or homeless) per 100 population. Age range: [20, 40].

Table A.5: Effects of any disasters in early-life years on labor force participation

	(1) Worker with any job	(2) Salary worker	(3) Full-time worker with any job	(4) Full-time salary worker
		Women		
In utero	-0.005	-0.001	-0.001	-0.001
	(0.004)	(0.002)	(0.002)	(0.001)
Birth year	0.005	0.001	-0.001	-0.001
	(0.004)	(0.002)	(0.002)	(0.001)
Age 1	0.001	0.003	-0.001	0.002
	(0.003)	(0.002)	(0.002)	(0.001)
Age 2	-0.007	-0.000	-0.001	-0.001
	(0.004)	(0.002)	(0.002)	(0.001)
		Men		
In utero	-0.007**	-0.004	-0.004	0.000
	(0.003)	(0.004)	(0.004)	(0.003)
Birth year	-0.004	0.003	-0.002	-0.003
	(0.003)	(0.003)	(0.004)	(0.003)
Age 1	-0.005	0.000	0.004	-0.003
	(0.003)	(0.004)	(0.004)	(0.003)
Age 2	-0.005	-0.001	-0.003	-0.001
	(0.003)	(0.004)	(0.004)	(0.003)
Age	Y	Y	Y	Y
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
Cohort FE	Y	Y	Y	Y

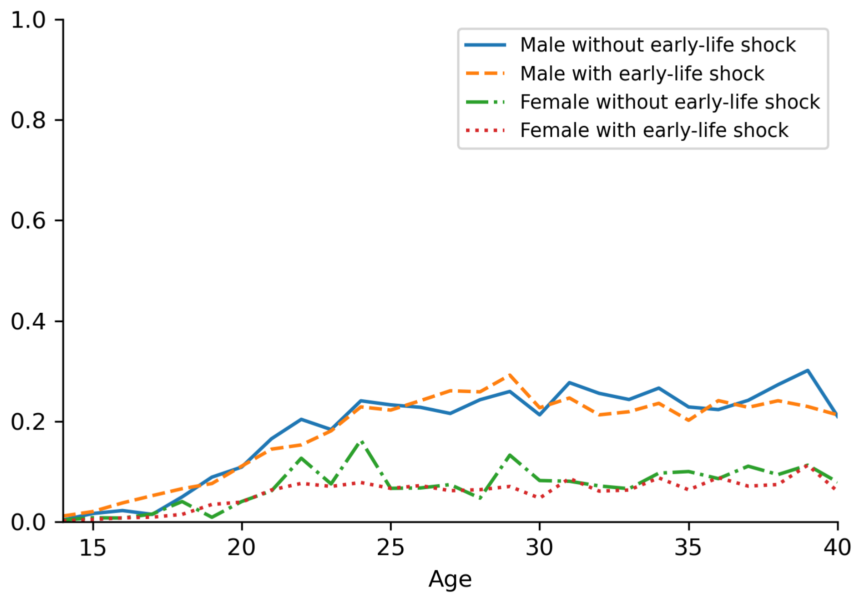
Note: This table shows regression results corresponding to Equation 4.1. Standard errors, clustered at the district level, are reported in parentheses. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level. The early-life disaster exposure measure is the number of disasters experienced from in utero to age two. "Any disasters" means that all events recorded in EM-DAT are considered. Age range: [20, 40].

Fig. A.1. Correlation between number of affected and number of deaths over population size



Note: This presents the correlation between two measures that can be used to define severe disaster: number of death per 1 million population, and number of people affected per 100 population which is used in the main analysis. Each dot is one disaster event. The regressions using two measures to define severe disasters show similar results.

Fig. A.2. Share of people working for salary paid monthly or annually over ages



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.”