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Impact of natural disasters on educational attainment in India: a panel data analysis

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Abstract
Natural disasters are known to adversely affect welfare, especially education. This can lead to a loss in human capital, reducing future growth and development. We use data from two of the latest rounds of the India Human Development Survey (IHDS) and employ a panel difference in difference regression model with continuous treatment fixed effects at the individual level. This allows us to examine the impact of natural disasters on education outcomes between 2004-05 and 2011-12 at the individual level. Our estimates improve upon all earlier studies on this theme that have relied on cross-section or pseudo-panel data at the district level. We provide first estimates of the impact of natural disasters on educational attainment disaggregated by social (including caste, religion, and gender) and economic groups (consumption quintiles). Natural disasters significantly and negatively affected education for women and three Consumption Quintiles (including those below poverty), Other Backward Castes, Scheduled Castes, Muslims, and other Minorities. We also find that the number of household assets, the number of children in the household, school fees, school type, Confidence intensity, health insurance, and life insurance influence educational years. Our results have significant implications in the context of quality education (SDG 4), gender equality (SDG 5), reduced inequalities (SDG 10), and climate change (SDG 13). The study evaluates the impact of the rising incidence of climate extremes vis-a-vis natural disasters as external shocks on educational outcomes. Educational attainment is directly linked to earnings and is well-established in the literature. We thus believe the negative impact of natural disasters on educational attainment, especially for the marginalized, may have long-term disruptive effects beyond immediate losses and may last through generations.

1 Introduction

Natural disasters have varied direct and indirect effects on human well-being [1–3], some of which have immediate consequences and long-term effects [4]. These include impacts on mental health [5], mortality and morbidity [6], economic growth [7], and financial status and consumption [8], among others. Some have found that only catastrophic natural disasters negatively affect output growth in the short or long run [7].

A growing international literature has examined the causal relationship between natural disasters and educational attainment [9, 10]. One of the long-term effects is the impact on human capital, specifically education [11, 12]. Earlier studies have examined the impact of natural disasters on school enrolment [13] and years of schooling as an indicator of

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human capital [14]. Natural disasters could have inter-generational effects, leading to lower human capital accumulation of such families across generations [15].

Education is seen as a form of investment in human capital that contributes to the development of economies. The creation and accumulation of human capital are often directly linked to reducing poverty and inequalities and increasing well-being [16]. Given the prominence of poverty, inequality, and social and identity barriers in developing nations, education is the key to breaking free for marginalized communities [17]. It is well-researched that these socioeconomic barriers have intergenerational consequences for the marginalized [18]. Ironically, these socioeconomic barriers also restrict the level and quality of education accessible to marginalized households. These issues are sought to be addressed through policy frameworks and decision-making in every developing economy at the micro and macro levels. Though natural disasters impact developed and developing nations, the latter face far more severe consequences arising from risky living conditions, lack of resources, debt, and socioeconomic barriers [19].

Given the challenges of overcoming social and economic hierarchies in accessing quality education (SDG 4) in developing nations, marginalized households are more vulnerable to any form of external shock [20]. Such are the challenges to marginalized households that are located in disaster-prone regions.

We provide the first estimates of the impact of natural disasters on educational attainment using a nationwide individual panel data set in India. Our results update all previous studies by using a differential level of exposure of individuals in the eligible age group to natural disasters between 2004-05 and 2011-12. We use data from two of the latest rounds of the India Human Development Study (IHDS) and employ a panel difference in differences (DID) regression model with continuous treatment and fixed effects at the individual level. This allows us to examine the impact of natural disasters on education outcomes between 2004-05 and 2011-12 at the individual level. We provide disaggregated results by gender, economic quintiles, caste, and religion. We find that natural disasters significantly and negatively affected education for women and three consumption quintiles (including those below poverty, BPL), Other Backward Castes (OBCs) and Scheduled Castes (SCs), Muslims, and Other Minorities. We also find that the number of household assets, the number of children in the household, school fees, school type, Confidence intensity, health insurance, and life insurance influence educational years. Our results have significant implications in the context of the Sustainable Development Goals (SDG), like quality education (SDG4), gender equality (SDG5), reduced inequalities (SDG10), and climate change (SDG13).

The rest of the paper proceeds as follows. Section 2 provides a brief literature review. Section 3 provides data and the method used for our analysis. In Sect. 4, we discuss and analyze our results. In Sect. 5, we provide a brief discussion. The paper concludes in Sect. 6.

2 Literature Review

The repercussions of exposure to natural disasters are profound, encompassing the loss of human lives and assets and the long-term impact on mental and physical well-being. Health risks associated with climate change events, such as natural disasters, are well-researched [21, 22]. Additionally, these events disrupt investments in physical and human capital, particularly in education [23]. These long-term effects of natural disasters on education pose a significant threat to marginalized communities [24]. Educational attainment significantly influences future earnings, with individuals experiencing up to 9 to 10 per cent private returns on investment in an additional year of education [25]. Exposure to natural disasters hamper learning and subsequently affects future earnings. Furthermore, these disruptions detrimentally affect gender equality in education, leading to lower enrolment, higher drop-outs, and reduced productivity [26, 27]. Although the global returns to education are reported to be higher for women, instances of domestic violence and early marriage, often followed by pregnancy in the aftermath of natural disasters, decrease the likelihood of girls completing their education [24]. Moreover, the physical loss of assets and resources often compels households to withdraw their children from school to assist with household chores or income-generating activities. [28] also suggests households adopting child marriage as a coping strategy to overcome their increasing vulnerabilities in the face of natural disasters. In conflict-affected societies, climate variability has also been found to have an association with the recruitment of children as soldiers in rebel groups [29]. Finally, extensive literature emphasizes the pivotal role of education in mitigating the effects of natural disasters and climate change [10, 30]. Therefore, the adverse educational outcomes for marginalized communities due to natural disasters would exacerbate losses from future exposure to such events. [31] highlights the impact of climate change on the education of children based on health, food security, school infrastructure, income, and migration in selected ASEAN Countries (Cambodia, Vietnam, Laos PDR).

Understanding the extent to which educational achievement among marginalized households is affected by natural disasters would enable more effective policy measures [11, 24, 32, 33].

Regions that experience more frequent occurrences of natural disasters could see higher investment for adaptation and mitigation, including relief [34, 35]. This could result in better school infrastructure (which is used during disasters as a relief centre) [36–38] and better educational attainment in the long run [39], as well as lower migration [40]. On the other hand, areas with high human capital could result in lower vulnerability among households exposed to natural disasters [10]. This could be due to better awareness and access to information, which minimizes losses from natural disasters [41]. More developed countries will likely deal with disasters better and experience fewer losses [42].

The research in this area has either focussed on the role of educational attainment in reducing vulnerability to natural disasters [43–46] or the impact of natural disasters on educational outcomes [11, 24, 31, 47, 48]. We follow the latter by estimating the impact of natural disasters on educational attainment in India. Most studies, however, are region or disaster-specific, like floods [49], droughts [50], and earthquakes [51, 52], among others. Some studies based on cross-section data [53] have the limitation that they do not observe the same households over time. Other studies have been region-specific [54] and lack the coverage of a national-level study.

Earlier studies have not examined how the frequency of natural disasters impacts education. Our study bridges this research gap by incorporating the frequency of natural disasters at a country level using individual longitudinal data with household and village characteristics. Such studies assume importance, especially for a large country like India, which is currently the most populous country in the world and is highly vulnerable to climate change-induced natural disasters [55, 56]. According to some estimates, almost 85 per cent of its geographical area is vulnerable to natural disasters [37].

Given India's vulnerability to climate change [56], the continuing challenge of access to marginalized section [57] and the role human capital plays in economic growth and well-being, it is essential to understand how natural disasters have impacted education attainment. This would be important for policymakers and communities trying to mitigate and adapt to climate change.

3 Data and method

3.1 Data

We use two waves of the India Human Development Survey (IHDS I and IHDS II, hereafter) that followed households over seven years [58, 59]. The first round (IHDS I) was conducted in 2004-05, and the second round (IHDS II) was conducted in 2011-12. It is the only national survey that provides longitudinal information on natural disasters and a wide range of socioeconomic characteristics with individual, household, and village-level identifiers. This survey provides information on natural disasters in India at the village level (rural) from 2006 to 2012. It also provides data on children's educational attainment (among other socioeconomic variables) at the household level.

The IHDS I [58] provides information for 215,754 individuals (belonging to 41,554 households in 1503 villages and 971 urban neighbourhoods), while IHDS II [59] has 204,565 individuals (belonging to 42,152 households in 1,503 villages and 971 urban neighborhoods across India).

This dataset provides identifiers from the individual, household, and village levels. Using these identifiers, we merged relevant data from the two rounds to get 150,995 individuals who had been interviewed in both rounds. The individual-level data were merged with household and village characteristics for both rounds, forming an elaborate panel dataset. Since the natural disaster data were collected only at the village level, we restricted our sample to rural households. To study variation in educational attainment, we further restricted the sub-sample to individuals between 6 and 23 years of age (to restrict the analysis to probable students who were still in the educational system or just exited).

3.2 Framework

We use a natural experimental study approach (Quasi-experimental design), using Natural Disasters as a continuous treatment to estimate the average treatment effect of natural disasters on Educational Attainment in India. A natural experiment takes a quasi-experimental design if that event is beyond the researcher's control [60]. Such approaches to program evaluation are most preferred in the absence of randomized control trials [14, 61]. An earlier study used this approach to estimate the impact of natural disasters on the well-being (measured by consumption expenditure) of households in India [62]. We follow this method by using a continuous measure of the frequency of occurrence of natural disasters (*Natural Disaster Intensity)*, trust in public institutions as *Confidence Intensity*, membership in various socioeconomic groups as *Membership Intensity* (a measure of social capital), and other covariates used by them to estimate the impact on educational attainment. In addition, we include *School fees*, *School Type (Government*, *Aided*, *Private)*, and *Repeated* (if an individual has ever repeated a class) as covariates to estimate their impact on Educational Attainment.

Multiple household and institutional characteristics determine educational attainment. These include household characteristics like household structure (proportion of children in the household) [63, 64], the nature of the household indicated by the ownership of household assets [65–67], and school type [68]. In our model, we incorporate an explanatory variable (*Natural Disaster Intensity*) measuring the cumulative effect of natural disasters on households between 2006 and 2012. These natural disasters are listed as floods, earthquakes, hailstorms, tsunamis, and droughts, among others). Past studies have recorded the role of gender [69], economic status [70], social groups [71], religion, and ethnicity in determining educational attainment [72].

The functional relationship that we wish to explore is as follows (see Eq. 1):

$$\begin{aligned} Education = f(&Natural\ Disasters\ Intensity\ (treatment), \\ &set\ of\ controls\ (Number\ of\ Children\ in\ Household, \\ &Number\ of\ Household\ Assets,\ Economic\ cost\ of\ education, \\ &Institutional\ type,\ Membership\ Intensity,\ Confidence\ Intensity, \\ &Financial\ resilience,\ Repetition\ of\ a\ class) \end{aligned} \tag{1}$$

In Eq. 1, education is the dependent variable measured in an individual's years of completed education, which depends on *Natural Disasters Intensity*, Household characteristics (*Number of Children in Household*, *Number of Household Assets)*, Economic cost of Education (School Fees) and Institutional type (Government, Aided and Private), *Membership Intensity* (construct to measure social capital), confidence in public institutions (construct to measure the level of trust in public institutions), Financial resilience (binary indicators for Life insurance and Health Insurance), and Repetition of class (a binary indicator for having repeated a class).

The structure of the difference-in-difference (DID) regression model can be illustrated as follows (see Eq. 2):

$$\begin{aligned} Y_i = \beta_0 + \beta_1 Time\_Period_{it} + \beta_2 Treated_{it} + \\ \beta_3 Time\_Period_{it} * Treated_{it} + \beta_4 Covariates_{it} + \varepsilon_{it} + uit \end{aligned} \tag{2}$$

In Eq. 2, $Y_i$is the observed value of the response variable, $Time\_Period_i$ is the time variable indicating the pre or post-treatment period, $Treated_i$ is the variable indicating treatment, $Time\_Period_i * Treated_i$ is the interaction term between *Time_Period* and the *Treatment*. $Covariates_i$ are a set of independent variables that possibly affect the response variable and $\epsilon_i$is the error term.

Our objective is to estimate the impact of natural disasters (with differential intensity) on educational attainment in households in rural India. We provide estimates disaggregated by *Gender* (Male and Female), *Consumption quintiles* (Below the poverty line (BPL) and five quintiles above the poverty line, from APL1 to APL5), Caste (General, Other backward castes, Scheduled castes, and Scheduled tribes) and *religion* (three categories -- Hindu, Other minorities and Muslim).

This disaggregation, we believe, would provide more robust estimates of the impact of natural disasters on educational attainment across different sections of the population.

3.3 Model

The basic intuition behind using a DID model is to evaluate the differences in the causal effect of an event between a treatment group (those affected by the event) and a control group (those unaffected by the event). In such a case, one could infer that if the event had never occurred, then differences between the treatment group and control group would have stayed the same. A natural disaster is a treatment similar to a 'natural program intervention.' In contrast to conventional DID models that use a binary treatment variable, we use a continuous treatment effect. This enables us to capture the slope effect (incremental change due to a unit increase in the intensity of the treatment, Natural Disasters) of the treatment in addition to the level effect. In other words, we could capture the marginal change in educational attainment for unit changes in the intensity of natural disasters.

The specification equation is stated as (Eq. 3):

$$\begin{aligned} Education_{it} = {} & a_0 + a_1\ Natural\ Disaster\ Intensity_{it} + a_2\ Number\ of\ children\ in\ Household_{it} + \\ & a_3\ Number\ of\ Household\ Assets_{it} + a_4\ School\ Fees_{it} + a_5\ Government\ School_{it} + \\ & a_6\ Aided\ School_{it} + a_7\ Private\ School_{it} + a_8\ Membership\ Intensity_{it} + \\ & a_9 Confidence\ Intensity_{it} + a_{10} Life\ Insurance_{it} + \\ & a_{11} Health\ Insurance_{it} + a_{12} Repeated_{it} + a_{13} Year_{it} + e_{it} + U_{it} \end{aligned} \tag{3}$$

where, *Education* = Years of Education. *Natural Disaster Intensity* = Ordered rank variable (range lies between 0 and 18). *Number of children in household* = number of children in the household. *Number of Household Assets* = number of household assets owned by the household. *School Fees* = School fees paid by households (in terms of 2011-12 values). *School Type* = type of educational institution (Others (1), Government (2), Aided (3), Private (4)). *Membership Intensity* = Ordered rank variable for household membership in one or more social or economic membership groups (range lies between 0 and 9). *Confidence Intensity* = Ordered rank variable for a household's level of confidence in public institutions (range lies between 10 and 30). *Life Insurance* = Dummy variable for financial resilience (Yes (1), No (0)) of household. *Health Insurance* = Dummy variable for financial resilience (Yes (1), No (0)) of household. *Repeated* = Dummy variable for an individual repeating the same class (Yes (1), No (0)). *Year* = Year indicator. ε_{it} = Residual.

3.4 Variables

The dependent variable (*Education*) is the number of years of completed education an individual has. This is expected to be influenced by a continuous treatment of *Natural Disaster Intensity*, constructed by aggregating various natural disasters and the frequency of their occurrences between 2006 and 2012. We include other controls such as the number of children in the household (*Number of children in the household*), school fees paid by the household (*School Fees)*, and the type of educational institutions: *Government* schools, *Aided* schools, and *Private* schools. The reference category (base level) included all other types of educational institutions (madrasa, convent, junior college, college, post-graduate, among others). We include a control *Repeated* to account for any individual repeating the same class.

We also added constructed variables such as *Membership Intensity* and *Confidence Intensity*. *Membership Intensity* represents the household's intensity in networking (a form of social capital) by counting household membership in one or more social or economic membership groups like membership in co-operatives, caste or religious groups, and self-help groups, among others. *Confidence Intensity* is a constructed variable depicting the household's confidence level in public institutions such as law enforcement, hospitals, and banks. Individuals' perceptions regarding their level of trust in public institutions were aggregated to create this variable. We also use binary indicators for *life insurance and health insurance to control* the financial resilience of the household.

4 Results

Table 1 provides the descriptive statistics for the variables used (see supplementary table S3 for the correlation matrix). An individual's average educational attainment is 5.41 years (overall standard deviation of 3.85). The average number of children in the household was 2 (overall standard deviation of 1.86 years), and the average intensity of natural disasters was 1.07 (overall standard deviation of 2.10). The range for natural disaster intensity lies between 0 and 18; zero is the lowest intensity (absence of natural disasters for the period in consideration), and 18 is the highest intensity. On average, school fees were 1465.36 (overall standard deviation of 6995.03).

We provide disaggregated estimates for the model with the fixed effects and control covariates by gender (Table 2) (see supplementary table S1 for random and fixed effect results panel results). To choose between the fixed effects model and the random effects model, we used the Hausman test (see supplementary table S2). First, the average treatment effect on treated (ATET) was negative and highly significant for females (-0.022). This indicated that females exposed to natural disasters experienced lower educational attainment. Secondly, the coefficient indicates that a unit increase in the *Natural Disaster Intensity* would lower the educational attainment of females exposed to natural disasters on average by *(0.02 years)*.

We also find that the *number of children in the household* negatively impacts educational attainment for males (-0.077) and females (-0.06). *The number of household assets* positively impacts educational attainment for males (0.02) and females (0.03). School fees had a positive impact on educational attainment for males and females. However, *Aided schools*

Table 1 Descriptive statistics

Variable		Mean	Standard deviation	Minimum	Maximum	Observations
Education	*Overall*	5.41	3.85	0.00	16.00	74,260
	Between		3.35	0.00	16.00	50,139
	Within		2.12	−2.59	13.41	1.48
Natural Disaster Intensity	*Overall*	1.07	2.10	0.00	18.00	66,763
	Between		1.73	0.00	18.00	47,301
	Within		1.34	−7.93	10.07	1.41
Number of children in the household	*Overall*	2.38	1.86	0.00	18.00	74,440
	Between		1.65	0.00	18.00	50,235
	Within		0.94	−5.62	10.38	1.48
Number of Household Assets	*Overall*	11.34	5.46	0.00	29.00	74,429
	Between		5.18	0.00	29.00	50,230
	Within		2.01	2.34	20.34	1.48
School Fees	*Overall*	1465.36	6995.03	0.00	860000.00	48,198
	Between		4822.34	0.00	433589.00	35,906
	Within		4520.78	−424945.60	427876.30	1.34
School Type	*Overall*	1.90	0.98	1.00	4.00	74,440
	Between		0.90	1.00	4.00	50,235
	Within		0.48	0.40	3.40	1.48
Membership Intensity	*Overall*	0.66	1.10	0.00	9.00	74,232
	Between		1.00	0.00	9.00	50,157
	Within		0.53	−3.84	5.16	1.48
Confidence Intensity	*Overall*	16.60	3.34	10.00	30.00	69,772
	Between		2.98	10.00	30.00	48,749
	Within		1.79	7.10	26.10	1.43
Health Insurance	*Overall*	0.07	0.25	0.00	1.00	74,360
	Between		0.22	0.00	1.00	50,201
	Within		0.14	−0.43	0.57	1.48
Life Insurance	*Overall*	0.21	0.40	0.00	1.00	74,395
	Between		0.37	0.00	1.00	50,217
	Within		0.20	−0.29	0.71	1.48
Ever Repeated	*Overall*	0.13	0.34	0.00	1.00	66,778
	Between		0.30	0.00	1.00	46,008
	Within		0.18	−0.37	0.63	1.45
Female	*Overall*	0.44	0.50	0.00	1.00	74,440
	Between		0.50	0.00	1.00	50,235
	Within		0.04	−0.06	0.94	1.48
Consumption Quintiles	*Overall*	1.97	1.65	0.00	5.00	74,425
	Between		1.50	0.00	5.00	50,227
	Within		0.77	−0.53	4.47	1.48
Caste Categories	*Overall*	2.16	1.07	1.00	4.00	74,403
	Between		0.92	1.00	4.00	50,225
	Within		0.63	0.66	3.66	1.48
Religion Groups	*Overall*	1.31	0.68	1.00	3.00	74,440
	Between		0.67	1.00	3.00	50,235
	Within		0.08	0.31	2.31	1.48
Year	*Overall*	2008.57	3.50	2005.00	2012.00	74,440
	Between		2.52	2005.00	2012.00	50,235
	Within		2.82	2005.07	2012.07	1.48
Age	*Overall*	13.93	5.00	6.00	23.00	74,440
	Between		4.59	6.00	23.00	50,235
	Within		2.69	5.43	22.43	1.48

Source: Author's calculation

Table 2 Disaggregated estimates of ATET by gender

Variables dependent: education	Male	Female
ATET		
Natural disaster intensity	−0.0136 (0.0089)	-0.0221^{**}(0.0095)
Controls		
Number of children in household	-0.0768^{***}(0.0175)	-0.0607^{***}(0.0166)
Number of household assets	0.0212^{***}(0.0064)	0.0313^{***}(0.0071)
School fees	−0.00000136 (0.0000)	0.000000552 (0.0000)
School type		
Government	0.0939 (0.0603)	0.0151 (0.0590)
Aided	0.236^{***}(0.0809)	0.323^{***}(0.0824)
Private	-0.195^{***}(0.0687)	-0.144^{**}(0.0706)
Membership intensity	0.00590 (0.0179)	−0.0120 (0.0178)
Confidence intensity	0.00527 (0.0049)	0.0115^{**}(0.0054)
Health insurance	0.0429 (0.0654)	−0.0195 (0.0690)
Life insurance	0.0851^{**}(0.0427)	−0.0124 (0.0444)
Repeated	-0.394^{***}(0.0555)	-0.433^{***}(0.0627)
Year (2012)	5.919^{***}(0.0531)	6.111^{***}(0.0555)
Constant	2.549^{***}(0.1301)	1.592^{***}(0.1381)
Number of observations	22,298	17,465

Source: Author's calculation

Standard errors in parentheses

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

positively affect educational attainment, and *Private* schools negatively impact educational attainment for males and females compared to the reference category. *Confidence Intensity* (0.012) positively affects female educational attainment, whereas the indicator of *Life Insurance* for households positively influences educational attainment for males.

We provide disaggregated estimates by consumption quintiles (Table 3). We find the ATET was negative and highly significant for BPL (-0.05), APL4 (-0.10), and APL5 (-0.06). This indicates that individuals from these consumption quintiles exposed to natural disasters experienced lower educational attainment. Secondly, we find that a unit increase in the *Natural Disaster Intensity* would lower the educational attainment of BPL (0.05 years), APL4 (0.10 years), and APL5 (0.06 years) compared to their respective control groups within consumption quintiles.

The *number of children in the household* has a negative and significant impact on educational attainment for BPL (-0.10), APL1 (-0.16), and APL5 (-0.15). The *Number of Household Assets* positively and significantly impacts the educational attainment of BPL (0.03) and APL1 (0.05). *School fees* positively and significantly impact educational attainment for APL1. In School Type, *Government school* is positive and significant for APL1 and APL4, except APL2, which is negative. *Private school*s are negative and significant for APL2. *Confidence Intensity* is positive and significant for BPL. *Health Insurance* is significant and negative for APL1, APL4, and positive for APL2. *Life Insurance* is negative and significant for APL4. *Repeated* is negative and significant for BPL and APL4.

Next, we provide disaggregated estimates by Caste (Table 4). The ATET was negative and highly significant for Other Backward Castes (-0.17) and Scheduled Castes (-0.15). Also, we find that a unit increase in the *Natural Disaster Intensity* would lower the educational attainment of these marginalized castes (Other Backward Castes by 0.17 years and Scheduled Castes by 0.15 years).

The *number of children in the household* significantly impacts educational attainment for Other Backward Castes (-0.16) and Scheduled Castes (0.26). The *number of household assets* positively and significantly impacts educational attainment for Scheduled Tribes. *School fees* were positive and significant for Scheduled Castes. In school types, *Aided schools* positively impact educational attainment for Scheduled castes and a negative for Scheduled Tribes. *Membership Intensity* is negative and significant for Scheduled Tribes. *Confidence intensity* is negative and significant for Scheduled Tribes. *Health insurance* is positive and significant for Other Backward Castes and Scheduled Tribes, and *Life insurance* is negative for Scheduled castes. *Repeated* is negative and significant for General and Other Backward Castes.

Finally, we provide disaggregated estimates by Religion (Table 5). The ATET was negative and highly significant for Other Minorities (–0.085) and Muslims (–0.089). Also, we find that a unit increase in the *Natural Disaster Intensity* would

Table 3 Disaggregated estimates of ATET by Consumption Quintiles

Variables dependent: education	BPL	APL1	APL2	APL3	APL4	APL5
ATET						
Natural disaster intensity	−0.0591**(0.0272)	−0.000462 (0.0362)	0.0692 (0.0446)	0.0367 (0.0417)	−0.101***(0.0388)	−0.0626*(0.0344)
Controls						
Number of children in household	−0.101***(0.0329)	−0.156**(0.0657)	−0.107 (0.0841)	0.0394 (0.0962)	0.149 (0.1570)	−0.149**(0.0608)
Number of household assets	0.0265*(0.0142)	0.0508**(0.0255)	0.000748 (0.0443)	0.0489 (0.0338)	0.0258 (0.0354)	0.00631 (0.0275)
School fees	0.0000520 (0.0000)	0.0000963**(0.0000)	0.00000915 (0.0001)	-0.00000980 (0.0000)	0.0000125 (0.0000)	-0.000000279 (0.0000)
School type						
Government	0.0867 (0.2019)	0.504**(0.2227)	−1.172**(0.4825)	0.312 (0.3020)	0.536**(0.2598)	0.0231 (0.2347)
Aided	0.196 (0.2556)	0.411 (0.2864)	−0.222 (0.5161)	−0.214 (0.3547)	0.252 (0.4545)	−0.0633 (0.4167)
Private	−0.150 (0.2591)	−0.0623 (0.3016)	−1.260***(0.4401)	−0.248 (0.3852)	0.186 (0.2413)	0.107 (0.1798)
Membership intensity	0.0303 (0.0615)	−0.106 (0.0694)	0.0560 (0.0964)	0.0138 (0.0696)	0.0697 (0.0677)	−0.00357 (0.0582)
Confidence intensity	0.0241**(0.0122)	0.00877 (0.0169)	0.0296 (0.0279)	−0.0193 (0.0260)	0.0207 (0.0235)	0.00450 (0.0227)
Health insurance	0.118 (0.1230)	−1.124*** (0.3673)	0.891***(0.2609)	0.267 (0.2277)	−0.463*(0.2755)	−0.192 (0.3250)
Life insurance	0.160 (0.1534)	−0.0426 (0.1940)	−0.0345 (0.2912)	−0.0111 (0.1799)	0.261*(0.1579)	−0.120 (0.1694)
Repeated	−0.464***(0.1156)	−0.0916 (0.1824)	−0.266 (0.2790)	−0.422 (0.2871)	−0.625**(0.2500)	0.0189 (0.4737)
Year (2012)	6.223***(0.1007)	5.749***(0.1823)	5.465***(0.2780)	6.098***(0.2728)	6.517***(0.3526)	5.948***(0.2172)
Constant	0.813***(0.2971)	2.258***(0.4505)	3.233***(0.8505)	1.835**(0.7172)	1.277***(0.4869)	3.803***(0.6294)
Number of observations	9325	7880	6774	6160	5295	4329

Source: Author's calculation

Standard errors in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 4 Disaggregated estimates of ATET by Caste categories

Variables dependent: education	General	Other backward castes	Scheduled castes	Scheduled tribes
ATET				
Natural disaster intensity	−0.0161 (0.0197)	−0.172*(0.0961)	−0.151**(0.0712)	−0.00598 (0.0794)
Controls				
Number of children in household	−0.0406 (0.0303)	−0.156*(0.0797)	0.257*(0.1552)	−0.0733 (0.2187)
Number of household assets	0.0199 (0.0155)	0.0463 (0.0371)	0.132*(0.0721)	−0.0266 (0.1034)
School fees	0.00000107 (0.0000)	−0.0000212 (0.0000)	0.000377**(0.0002)	−0.0000220 (0.0001)
School type				
Government	0.143 (0.1209)	−0.501 (0.4169)	0.900 (0.8627)	−0.530 (0.7248)
Aided	0.147 (0.1966)	−1.085 (0.8591)	1.637*(0.9016)	−1.424**(0.6681)
Private	−0.0861 (0.1284)	−0.548 (0.4475)	0.188 (0.9199)	−0.697 (0.6287)
Membership intensity	−0.0323 (0.0443)	0.00304 (0.0997)	−0.344 (0.2678)	−0.789***(0.2324)
Confidence intensity	0.0104 (0.0108)	0.0144 (0.0294)	0.0381 (0.0741)	−0.175**(0.0789)
Health insurance	−0.135 (0.1245)	1.435***(0.4309)	0.361 (0.4312)	1.493*(0.8678)
Life insurance	−0.0463 (0.0848)	−0.162 (0.3112)	−1.363**(0.5538)	−0.447 (1.0419)
Repeated	−0.531***(0.1254)	−0.749**(0.3039)	0.0553 (0.4897)	1.106 (0.9725)
Year (2012)	6.137***(0.1072)	5.889***(0.2597)	6.490***(0.3805)	6.352***(0.5139)
Constant	2.765***(0.2810)	2.150***(0.8158)	−2.131 (2.0478)	7.316***(1.8593)
Number of observations	14,017	12,506	6432	6808

Source: Author's calculation

Standard errors in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

lower the educational attainment of these religious minorities (Other Minorities by 0.085 years and Muslims by 0.089 years).

The *number of children in the household* negatively and significantly impacts educational attainment for all religions. The *number of household assets* positively and significantly impacts educational attainment for Hindus and Muslims. *School fees* negatively and significantly impact educational attainment for other minorities. In school types, *Government schools* are seen to impact educational attainment for other minorities positively, *Aided schools* have a positive impact on educational attainment for Hindus, and *Private schools* are seen to impact educational attainment for Hindus and Muslims negatively. *Confidence intensity* is positive and significant for Hindus. *Health insurance* is positive and significant for other minorities. *Repeated* is negative and significant for Hindus and Other minorities.

5 Discussion

We find consistent evidence that *Natural Disaster Intensity* has a negative and significant effect on the educational attainment of those exposed to natural disasters. Our results are similar to many others, like [33] and [49], who studied the impact of flooding on education to find that years of schooling dropped by 0.2 years and a negative relationship on test scores ranging between 0.03 and 0.11 standard deviations in China and Thailand, respectively. In the case of earthquakes [51], found a higher probability of drop-outs (2.8 per cent higher in post-earthquake) and lower on-time graduation (-6.6 per cent lower in post-earthquake) [52]. finds that children born in areas prone to earthquakes have a 13.8 per cent and 10 per cent lower probability of completing middle school and high school, respectively. Our findings with disaggregated estimates add to this literature. We find consistent adverse impacts for females, three consumption quintiles (BPL, APL4, and APL5), two marginalized caste categories (OBC and SC), and religious minorities (Muslims and Other minorities). After controlling for other factors, we find that a unit increase in natural disaster intensity reduces educational attainment for females by 2.2 per cent for three consumption quintiles (BPL, APL4, and APL5 by 5.9 per cent, 10.1 per cent, and 6.26 per cent, respectively) for two marginalized castes (OBC and SC by 1.72 per cent and 1.51 per cent respectively), and religious minorities (Muslims by 8.9 per cent and other minorities by 8.5 per cent).

Table 5 Disaggregated estimates of ATET by Religion

Variables dependent: education	Hindu	Other minorities	Muslim
ATET			
Natural disaster intensity	−0.00697 (0.0068)	−0.0852** (0.0389)	−0.0892*** (0.0253)
Controls			
Number of children in ousehold	−0.0507*** (0.0132)	−0.158*** (0.0455)	−0.154*** (0.0429)
Number of household assets	0.0257*** (0.0051)	0.0275 (0.0184)	0.0553*** (0.0187)
School fees	0.000000423 (0.0000)	−0.00000125** (0.0000)	0.0000150 (0.0000)
School type			
Government	0.0741 (0.0459)	0.439*** (0.1577)	−0.122 (0.1859)
Aided	0.278*** (0.0614)	−0.00913 (0.2798)	0.170 (0.3008)
Private	−0.140** (0.0548)	−0.154 (0.1797)	−0.444** (0.1803)
Membership intensity	−0.00633 (0.0134)	0.0115 (0.0664)	0.00223 (0.0450)
Confidence intensity	0.00846** (0.0038)	0.0235 (0.0175)	0.00353 (0.0146)
Health insurance	0.0164 (0.0491)	0.377** (0.1851)	−0.310 (0.2706)
Life insurance	0.0530 (0.0327)	−0.190 (0.1255)	0.0409 (0.1368)
Repeated	−0.456*** (0.0434)	−0.374** (0.1690)	−0.0228 (0.2080)
Year (2012)	6.064*** (0.0414)	5.888*** (0.1498)	5.432*** (0.1514)
Constant	2.064*** (0.1020)	2.380*** (0.4155)	1.991*** (0.3595)
Number of observations	32,846	2948	3969

Source: author's calculation

Standard errors in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

We also find that the number of children in the household negatively and significantly impacts educational attainment for both genders, consumption quintiles (BPL, APL1, and APL5), social groups (OBCs), and all religions. The *number of household assets* has a positive and significant impact on educational attainment for both genders, consumption quintiles (BPL and APL1), social groups (SCs), and religion (Hindus and Muslims). This aligns with the extensive literature on the links between household assets (financial and non-financial) and educational attainment [73].

We find that *School fees* have a positive and significant impact on educational attainment for consumption quintiles (APL1) social groups (SCs) and a negative and significant impact on religion (other minorities). Earlier studies have found that higher college fees led to a rise in degree completion [74] but reduced enrolment [75]. We, however, do not test for changes in enrolment.

Apart from school fees, we also looked at *school type* since it captures additional indicators beyond school fees, including the learning atmosphere. In *the school type category*, our reference category was other schools. We find that *Government* and *Aided* schools had a positive and significant impact on educational attainment across gender, consumption quintiles (except APL2, which is negative), caste (Scheduled castes, but negative for Scheduled Tribes), and religion (Hindus). On the other hand, *Private* schools negatively impacted educational attainment for both genders, APL2, Hindus, and Muslims.

Membership Intensity negatively and significantly affects Scheduled Tribes. Confidence Intensity positively and significantly affects women, BPL, and Hindus, whereas it negatively affects STs. Financial resilience in the form of Health insurance positively and significantly affects APL3 and other minorities, whereas it negatively affects APL1 and APL4, OBCs, and STs. Financial resilience in the form of Life Insurance positively and significantly affects men, APL4, whereas it negatively affects Scheduled Castes. Repeating in a class negatively and significantly affects both genders, BPL and APL4, general and Other Backward Castes, and Hindus and Other minorities.

6 Conclusion

The United Nations' disaster risk reduction and resilience platform links 10 of the 17 SDGs to natural disasters (SDGs 1,2,3,4,6,9,11,13,14 and 15). Our findings reaffirm that climate change (SDG13) and natural disasters significantly negatively affect educational attainment. This is more severe for marginalized sections (women, BPL, OBCs, SCs, minority religions). On the one hand, lower educational attainment (SDG4) in disaster-prone areas could trigger a chain of disruptive welfare effects in the form of lower overall earnings (SDG8), widening of gender differences (in attainment and earnings) (SDG5), and higher societal inequalities (SDG10). On the other, these lower educational attainments reduce the effectiveness and increase the cost of disaster management programmes developed for mitigation from natural disasters and reduce vulnerabilities. Studies have shown that higher education levels lead to better awareness levels and ease of information dissemination and serve as a measure of development with direct and indirect effects on reducing fatality rates [41].

Additionally, higher educational attainment will help motivate pro-climatic behaviour [43]. The higher vulnerability combined with the increasing frequency of natural disasters in recent times and the inability to migrate leaves the marginalized in danger of intergenerational disruptions in well-being. It could create a spiral of lower education, earnings, and welfare, inevitably pushing them to poverty. Climate change policy must address these developmental challenges to build a resilient society.

Limitations

The IHDS dataset offers self-reported data on disasters, and thus, there is a potential risk of self-reporting bias in the data. However, since the disaster data was collected at the village level and education data at the household level, the likelihood of bias impacting our results is limited. The information we had access to lacked details on disaster relief efforts and external aid after the disaster. This could influence the impact of disasters on households. Further, we had information over only two rounds. As and when more data becomes available, this would lend itself to a richer analysis. Our study was limited to understanding the impact on education attainment. Future research could focus on the implications of natural disasters for employment and earnings, health, and asset ownership. This would inform policies on climate change vulnerability and address resilience plans. Our study offers a country-wide analysis. However, much of the governance interventions occur at the level of states or regions. A disaggregated study at the state or regional level would help design targeted policies.

Author contributions YR and PM conceptualised the study. They designed the computational framework together. They also designed the model and undertook the data analysis. YR performed the calculations. YR and PM wrote the manuscript. The first draft of the manuscript was jointly written and both authors read and approved the final manuscript.

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Data availability We use publicly available sources that all users can access. All data is referred to in the text. The data supporting this study's findings are available in the IHDS public data files from the Data Sharing for Demographic Research program of ICPSR, the Inter-university Consortium for Political and Social Research. These can be obtained at the respective webpages of the ICPSR Study 22626 (India Human Development Survey (IHDS), 2005 https://www.icpsr.umich.edu/web/DSDR/studies/22626*)* and ICPSR Study 36151 (India Human Development Survey-II (IHDS-II), 2011-12 https://www.icpsr.umich.edu/web/DSDR/studies/36151*)*.

Code Availability The codes used for the analysis will be made available on request.

Declarations

Ethics approval and consent to participate This article does not contain any studies with animals performed by any of the authors. The data from human respondents was drawn from a publicly available, fully anonymized database.

Competing interests The authors declare no competing interests.

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