Floods and Children's Education in Rural India

Nazar Khalid, Jere Behrman, Emily Hannum, and Amrit Thapa

Floods cause extensive damage in high-income countries, including the United States, but problems are more severe in low- and middle-income countries (LMICs) that lack preventative and mitigating infrastructure. Marginalized children's education in LMICs might be particularly vulnerable. Using the Indian Human Development Survey, we investigate flood exposure implications for the education of school-age rural children, paying particular attention to children from marginalized groups. Results show that lower-caste Hindu, Muslim, and poorer children with less-educated parents in agricultural households are more likely to experience flooding. Interactions between flooding and marginalization characteristics indicate that flood exposure is associated with disproportionately negative learning outcomes for girls and that economic resources may mitigate flood exposure effects on delayed school progress. While greater exposures for marginalized groups are concerning, the limited number and modest magnitudes of documented negative effect heterogeneities for marginalized children are somewhat better news.

Keywords: floods, rural education, socioeconomic stratification, caste, religious stratification, India

With climate change, flood frequency is increasing across the globe. Water-control systems are often inadequate for changing climatic conditions. Growing populations induce greater use of marginal lands with elevated flood vulnerability. The 2021 German floods demonstrate that effects can be catastrophic even in a high-income country known for

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strong infrastructure. Flooding is the most ubiquitous and costly natural hazard in the United States (Grimm 2020). The cost of flood damage in the United States was approximately $17 billion annually between 2010 and 2018, according to testimony from Federal Emergency Management Agency representative Michael Grimm (Grimm 2020; Duguid 2021). Although most of these costs as usually estimated are physical destruction, considerable foregone human-resource investments are possible in general and in terms of children's education, in particular. In recent times, Hurricane Sandy on the East Coast, Hurricane Maria in Puerto Rico, Hurricane Harvey in Texas, Hurricane Ida in Louisiana, and Hurricane Ian in Florida have had devastating implications for educational systems (Brusi and Godreau 2019; Chakrabarti and Livingston 2012), and vulnerability to flood exposure varies across subpopulations (Lieberman-Cribbin et al. 2021).

Marginalized groups tend to be relatively vulnerable to flooding and other climatic disasters across national settings, but wealthier countries are more likely to have the infrastructure and financial resources to limit disastrous effects and to support recovery, while poorer countries have fewer available avenues for prevention and recovery (Carty and Walsh 2022; see also Eckstein, Künzel, and Schäfer 2021). As climate change has escalated, problems in poorer countries have mounted. Oxfam estimates that funding requirements for UN humanitarian appeals linked to extreme weather are now eight times higher than they were twenty years ago, and that over the past five years, such appeals were only 54 percent funded on average, resulting in an estimated funding shortfall of $28 to $33 billion (Carty and Walsh 2022, 3).

In this context, high-income countries such as the United States are likely to face increasing pressure to divert foreign aid from development assistance to disaster protection and relief as climate-related damage grows (Harbeson and McCormick 2021). This shift is already happening: the Biden-Harris administration has committed to addressing the climate crisis abroad as a core element of national security and foreign policy, involving diplomatic engagement as well as foreign assistance (White House 2021a, 2021b). A recent White House Press Briefing states that the United States "has a compelling national interest in strengthening global protection for individuals and groups displaced by the impacts of climate" and that particular concern needs to be given to the disproportionate impact, globally, on marginalized communities (White House 2021b).

South Asia is a highly populated, geopolitically significant region that is also one of the most vulnerable to climatic shocks (World Bank 2022). The World Bank reports that more than half of all South Asians, approximately 750 million people, were affected by climate-related disasters in the last twenty years, and that climate change "could sharply diminish living conditions for up to 800 million people in a region that already has some of the world's poorest and most vulnerable populations" (2022). Floods that covered about a third of Pakistan in 2022 are a vivid illustration of these risks. An important mechanism through which diminishment in living conditions could occur, but one that is not yet well understood, is by disruptions in children's human-capital development (Benson and Clay 2004).

India is a particularly important case. It is ranked seventh in the 2021 global climate-risk index (Eckstein, Künzel, and Schäfer 2021, 7); has experienced secularly increasing floods and flood damage; is home to the world's largest number of school-age children; and is highly stratified along caste, religious, and socioeconomic lines. The majority of Indian children live in rural communities, where floods can hinder education by causing school closures, disrupting transportation systems, damaging school infrastructure, increasing child-labor demands to deal with fallout from floods and flood damage, and otherwise disrupting local activities. Consequences could include reduced enrollment and attendance, leading to slower grade progression and worse learning outcomes. The educational effects of flooding, moreover, might be heterogeneous, due to either disparate exposures or disparate buffering, with respect to child and family characteristics such as gender, age, religion, caste, and socioeconomic status.

This article considers flooding impacts on Indian children's education, with particular focus on heterogeneous impacts on the most marginalized school-age rural child populations. We use the Indian Human Development Survey (IHDS), a nationally representative panel survey that collected data on learning, in addition to more standard information on school enrollment and educational attainment. The IHDS permits investigation of the heterogeneous effects of floods on the educational progress and learning of rural children ages eight to eleven years.

We consider two questions: Are children from marginalized groups disproportionately exposed to floods? Do children from marginalized groups experience disproportionate negative educational effects, when exposed?

BACKGROUND

Natural disasters such as floods are expected to increase in frequency and intensity as a result of climate change over the next few decades and to affect a sizable portion of the global population (Hirabayashi et al. 2013; Scheuren et al. 2008). In studying the impact of disasters on people's lives, social scientists make a distinction between disasters as discrete environmental events that occur when a hazard is realized and disasters as social processes (Arcaya, Raker, and Waters 2020; Frankenberg, Laurito, and Thomas 2014). Extreme rainfall and floods affect millions of people by their adverse impacts on physical, financial, and human capital, and disruptions to economic activity, consumption, employment, and investment (Benson and Clay 2004). Interest among social scientists is strong in investigating the ways that different social groups experience climate risks and environmental exposures unequally (see Rauscher and Cao 2024, this issue). To gain a better understanding of the social roots of the impacts of such disasters, studies frequently use the concepts of vulnerability and resilience (Frankenberg et al. 2013). Existing inequalities along lines of gender, age, race, caste, religion, and socioeconomic status may all be important factors in determining who is most vulnerable to disasters and who is most resilient (Enarson 2012).

Given their high exposure, greater sensitivity to certain exposures, and reliance on caregivers, children are particularly vulnerable to negative environmental adversities (Ebi and Paulson 2007; Frankenberg and Thomas 2017; Walker et al. 2007). Research suggests that in low- and middle-income countries (LMICs), children are frequently the first and the most affected victims of environmental shocks (Martin 2010; Norris et al. 2005). Recurrent and extreme floods can affect children in multiple ways. Flooding can cause immediate physical harm. Flooding can also cause physical damage to the school and health-care infrastructure, disrupting education and limiting access to proper medical care. Similarly, floods increase the likelihood of households falling into poverty, which might be particularly significant for households that depend on natural resources for a living. In many LMICs, income loss, asset loss, and increased disaster-related expenditures can create pressure on families to remove their children from school to enable them to work instead. Financially strapped families may be unable to afford adequate medical care, food, or school supplies, all of which have negative impacts on children. Households may reduce food consumption due to income losses, which can raise risk of child malnutrition and stunted growth (Dimitrova and Muttarak 2020; WHO and de Onis 2006). Finally, trauma caused by such events can cause deterioration in mental health, which can affect physical health and academic achievement (Frankenberg and Thomas 2017).

Despite the realization that weather shocks have multiple effects on a wide range of indicators of children's well-being, research in LMICs continues to be almost exclusively focused on nutritional and health outcomes (Currie and Vogl 2013; Frankenberg et al. 2008; Rosales-Rueda 2018). Relatively few studies have investigated the schooling and educational attainment of children living in flood-prone areas, even though, according to EM-DAT (2021), floods are the most frequently reported natural disaster worldwide.

Emergency school closures and disruptions, which are common due to unpredictable, recurrent, and severe floods, can have significant adverse impacts on children's education. Studies of high-income countries have found that emergency school closures and other educational disruptions are associated with increased dropout (Azevedo et al. 2021). Further, interrupted learning due to unscheduled school closures has been found to have negative impacts on test performance (Marcotte and Hemelt 2008).

Because destruction caused by disasters is a function of the events themselves, where and how societies build, and the resources available to recover and respond, children in LMICs feel adverse impacts to a far greater extent than adults (Kousky 2016). Uninsured extreme-weather shocks can have significant and long-lasting effects on children's human capital because low-income households are unable to protect their consumption of food, health, and education (Baez, de la Fuente, and Santos 2010). Xin Meng and Robert Gregory (2002) examined the impacts of school closures on children's educational attainment during China's Cultural Revolution. They find that interrupted learning because of frequent junior- and senior-high-school closures reduced children's chances of getting formal four-year university degrees by about 55 percent (Meng and Gregory 2002, 953). Kawin Thamtanajit (2020) finds that Thai children who were exposed to recurrent floods that resulted in months of school closures and destruction of basic school facilities performed worse on tests than children who were not exposed to such events. Floods in Madagascar reduced the likelihood of teenagers attending school, encouraging them to enter the labor market (Marchetta, Sahn, and Tiberti 2019). Girls had much higher chances of dropping out and entering labor markets than boys. In general, natural disasters are likely to exacerbate the learning crisis in LMICs, where roughly half of children are already failing to acquire required foundational skills (World Bank 2019).

The Indian Context

India's geophysical and climatic features make it one of the world's most disaster-prone countries (Patankar 2019). India's population has become more susceptible to flooding as a result of climate-change-induced increases in extreme precipitation events and ongoing population growth (Ali, Modi, and Mishra 2019). Floods have accounted for more than half of all natural and climate-related disasters in India since the 1990s (Patankar 2019). Floods have the potential to destroy crop and livestock production and thereby to jeopardize food security. Particularly vulnerable to this effect pathway are rural Indians, who account for nearly three-quarters of the population (Dimitrova and Muttarak 2020). Between 1980 and 2017, India experienced 278 floods, affecting more than 750 million people and causing an estimated $58.7 billion in damage (EM-DAT 2018). Strikingly, views are mixed on whether the past few decades of human development and economic growth have made India more resilient to the negative effects of floods (Bahinipati and Patnaik 2020; Parida 2020; Patri, Sharma, and Patra 2022).

Despite rapid recent economic growth, Indian children have some of the worst health and well-being indicators globally (Coffey et al. 2013). For example, in 2015, India had one of the highest rates of childhood malnutrition, and 38 percent of children under the age of five showed stunted growth patterns (Khan and Mohanty 2018). These conditions have implications for human-capital accumulation and capability development, and for resiliency in times of stress (Coffey et al. 2013). India also has the largest number of school-age children in the world, and many of these children live in rural areas of northern and eastern states prone to flooding. Anna Bertho and her colleagues (2012) find that flood-induced school closures varied between fifteen days to six months, with a median of three months, in highly flood-prone districts of Uttar Pradesh and Bihar, the two most populous states in India. Further, floods had a negative impact on education by making transportation to schools difficult or impossible, damaging school infrastructure, and otherwise disrupting local activities (Bertho et al. 2012). In a community-based study, Revathi Krishna, Kevin Ronan, and Eva Alisic (2018) find that many children whose studies were disrupted by severe floods explained that their return to school after the floods was inhibited because of illness or loss of books and uniforms. This article adds to limited existing research by providing a national-scale snapshot of the groups most vulnerable to flood exposure among rural children in India, and by investigating the implications of flood exposures for rural children's educational outcomes, overall and across social groups.

Social Groups and Inequality

Along with gender and socioeconomic status, other important social group identities are critical to understanding social stratification in India. Caste, tribal status, and religion are key dimensions. Historically, the Hindu caste system was a division of individuals into hierarchical groups and subgroups based on occupation, which in turn was rigidly related to notions of ritual purity, privilege, and social status (Deshpande 2011; Vaid 2014). The lowest classification in this hierarchy referred to groups historically consigned to ritually polluting, dirty, and degrading occupations. Members of this group were previously referred to by terms now considered pejorative; they are referred to in the Indian Constitution and in current official documents as Scheduled Castes. Although the Indian caste system was abolished in 1950, caste continues to be a powerful marker of individual identity. Members of Scheduled Castes continue to face overt and covert forms of discrimination, abuse, humiliation, and violence (Coffey et al. 2018; Hathi et al. 2018). Most of the two hundred million people belonging to Scheduled Castes are very poor, with limited access to social and economic resources (Deshpande 2011).

Scheduled Tribes, also known as *adivasis,* are members of Indigenous or tribal groups whose identities are often considered outside the Hindu caste system. These groups number more than 104 million in population and often live in remote parts of the country; they continue to experience economic and educational deprivations (Kumar, Pathak, and Ruikar 2020; Maharatna 2000). Religious minorities also sit outside the traditional Hindu caste system. India is home to the world's third-largest Muslim population, at more than 176 million (World Population Review 2023). Muslims are the largest minority religious group in India. They rank close to Scheduled Castes in terms of human-development outcomes and face social, economic, and political discrimination (Asher, Novosad, and Rafkin 2018; Hathi et al. 2018; Jaffrelot and Gayer 2012; Sachar et al. 2006). Moreover, although Scheduled Castes have rights to certain preferential policies and programs, few such programs are open to Muslims (Sachar et al. 2006; on the vulnerability of the Muslim population, see Fazal 2020).

DATA AND METHODS

Our sample includes children in rural households in the India Human Development Survey. The IHDS is a nationally representative multi-topic survey of more than forty-one thousand households in 971 urban blocks and 1,503 villages (Desai, Vanneman, and NCAER 2019). It is a panel survey with interviews conducted in 2004–2005 and in 2011–2012.

Dependent Variables

The IHDS collected information on current enrollment, highest grade completed, and other key information related to all members of the interviewed households. For children ages eight to eleven, the IHDS also administered learning, math, and writing assessment modules. Our analysis uses three measures of children's learning outcomes from 2011 to 2012. The first measure, grade-for-age, is defined as $grade/(age - 6)$, where grade is completed grades of education, age is a child's reported age, and six is the typical age children are when they complete the first grade.[1]

Our other two outcome measures come from IHDS's assessment of children's math and reading skills. The IHDS ranked children's performance on a math test from 1 to 4 in increasing order of math skills—cannot recognize numbers, able to recognize numbers, able to do subtraction, and able to do division. A similar ranking of 1 to 5 was used for performance on a reading test, with numbers referring, respectively, to children who could not recognize letters in the alphabet, could recognize letters in the alphabet, could read words, could read paragraphs, or could read stories. Both tests were based on standardized test modules de-

1. We use six to indicate that children complete their first grade by this age. However, studies on schooling in India tend to use both six and seven (Sahoo 2017; Desai and Kulkarni 2008).

veloped with the help of PRATHAM, an educational NGO, and are widely used in assessing learning among children in many contexts (Desai et al. 2010). Tests were translated into regional languages to facilitate easy administration and reduce anxiety levels among children. For the multivariate analysis of test score outcomes in tables 4 and 5, we standardized the test scores for each year of age to better facilitate interpretation of the estimates. In these tables, the outcome is defined as the number of standard deviations (SD) each child's test scores are above or below the mean of the test score distributions for children of the same age.

In the IHDS, the learning assessment tests were administered at home. For this reason, unlike analyses based on tests administered in schools, our analysis is not subject to selectivity bias due to school enrollment or attendance. Access to test score data means that our investigation goes beyond most studies to consider learning, rather than just time spent in school.

Independent Variables

The IHDS had a separate village module assessing various aspects of the local community, including information on village-level year-wise flooding histories for each year between 2006 and 2011. To minimize the problem of recall bias, the survey asked multiple informed citizens to report on the occurrence of floods for each year between 2006 and 2011. We defined a dichotomous measure of village flood exposure, with a value of 1 if the village was exposed to floods at least once during this period, and 0 if it was not. We also defined a state-level flood exposure measure as the fraction of villages in the state exposed to floods at least once during the period.

The IHDS includes rich characterizations of demographic and household characteristics: children's gender and age, caste, religious affiliation, household income, whether the main source of household income was agricultural, and parental educational attainments. These variables permit the investigation of differences in flood burdens on children's learning outcomes by potentially important stratifiers. Last, in a subset of our models for math and reading, we also include grade-for-age to explore whether falling behind in grade progression might be a mediating mechanism for flooding effects on learning.

Second-Wave Test-Taking Propensity Weighting

Estimated flood effects on educational outcomes could be biased by selective migration out of flood-prone areas. To reduce potential bias due to children not taking the second-wave survey tests, we adjust our estimates using a new set of weights constructed from each child's propensity to take the tests in the second wave. Despite its limitations, such propensity reweighting is a widely employed method for adjusting for survey nonresponse (Chen et al. 2015; Wun et al. 2007). We compare data from both waves to identify all children in the first wave who would have been between eight and eleven in the second wave and hence eligible for being administered the second-wave learning tests. This group included those who were administered the second-wave learning tests, those who were present in the second wave but did not take the tests, and those not present in the second wave. The propensity scores (or the predicted probability of taking the second-wave test) are estimated by a logistic regression of whether a child was tested in the second wave on village flood exposure, the fraction of villages exposed to the floods in the state between waves and first-wave values for gender, age, caste/religion group, income quintiles, main income source of the household, mother's and father's education, and total households in the village. We calculate final weights by multiplying the inverse of propensity to take the second-wave tests with the sample-design weights from the first wave of the IHDS.

Analytic Approach

First, we consider whether exposure to floods differs by groups defined by children's gender and ages, caste or religion, income quintile, whether agriculture is main income source, and parental education. Second, we estimate a series of ordinary least squares (OLS) regressions with each of three dependent variables—grade-for-age, math skills, and reading skills. For each outcome, we begin by estimating equation (1)—a main-effects model denoted as model (1) in the tables:

$$Outcomes = \alpha_1 + \beta_1 vfe + \beta_2 sfe + \beta_3 g + \beta_4 age + \beta_5 sg + \beta_6 iq + \beta_7 msi + \beta_8 meduc + \beta_9 feduc + \varepsilon \quad (1)$$

The right-side variables in this model are village flood exposure (*vfe*), state flood exposure (*sfe*), children's gender (*g*) and age (*age*), social (caste or religion) group (*sg*), household-income quintile (*iq*), household main source of income (*msi*), mother's (*meduc*) and father's (*feduc*) grades of education, and a random term (ε).

For each outcome, a second specification, model (2) in the tables, adds interactions of each of the main-effects variables with the village flood-exposure variable. This specification allows us to investigate whether the impact of floods on education differs by social group, children's gender and age, income quintiles, whether agriculture is the main income source, and parental education. A third specification, model (3) in the tables, incorporates village fixed effects along with interactions. Adding the village fixed effects allows us to account for fixed factors at the village level between the two survey waves that were not included in the models but might also be associated with children's learning. For instance, using village fixed effects helps account for the fact that children with better resources are likely to live in villages that are less flood exposed or have access to better schools. This is our preferred specification. Finally, a fourth specification, model (4), is estimated in the tables for the math and reading tests. Model (4) adds grade-for-age and its interaction with village flood exposure to model (2), with main effects and the interactions of the main effects with the village flood exposure. This specification allows exploration of whether grade-for-age is a mediating mechanism through which floods affect learning in the interaction model.

RESULTS

Table 1 presents descriptive statistics of the raw data for children ages eight to eleven years old in the IHDS second wave. Indian children typically are in grades two through six during these ages. The mean score of 2.33 in math suggests that an average child did better than recognizing numbers but was unable to do basic arithmetic operations such as subtraction. A mean score of 3.33 in reading implies that an average child could read words but had difficulties reading an entire paragraph. The mean grade-for-age below 1.0 suggests that, on average, rural children have completed fewer grades relative to age than they would have were they to enter school on time and progress one grade each year.

One-third of the children lived in villages that were exposed to floods between 2006 and 2011. On average, 35 percent of villages in each state were exposed to floods during this period. The mean age in the sample is 9.5 years and 48 percent are girls. Hindu Scheduled Castes, Scheduled Tribes, and Muslims—groups that have been historically marginalized and discriminated against— are 46 percent of the sample. Hindu Other Backward Castes, an officially recognized collection of castes that have remained socioeconomically poor, are 38 percent of the sample. The most privileged caste and religious group, Hindu Upper Castes, are 14 percent of the sample. One percent of children belong to non-Hindu-and-Muslim identities—classified here as "Other." More than half of the children belong to households with incomes in the lowest two income quintiles. Agriculture is the main income source for 57 percent of our sample households. Fathers of children averaged 5.2 grades of education, two more grades than their mothers, who averaged 3.2 grades.

Vulnerability Across Background Characteristics

Table 2 presents sample distributions of flood exposure by background characteristics. No differences by gender or age are significant. Among social groups, Hindu Other Backward Castes, Muslim, and Hindu Scheduled Caste children are most likely to be exposed to floods. Scheduled Tribes and Indigenous children tend to live in forests or hilly regions with relatively low flood exposure. Children in higher household-income quintiles and with higher parental education are less exposed to floods. Children from agricultural households are more likely to be living in flood-prone villages.

Table 1. Summary Statistics of Rural Children, Ages Eight to Eleven, for Variables Used in Regression Analysis

	Mean/Proportions	Std.
Outcomes		
Math[a]	2.33	0.96
Reading[b]	3.32	1.42
Grade-for-age[c]	0.94	0.45
Flood exposure		
Village flood exposure[d]	0.33	0.47
State flooding index[e]	0.35	0.17
Demographic characteristics		
Female[f]	0.48	0.50
Age (years)	9.50	1.08
Caste or religion		
Hindu Upper Castes	0.14	0.35
Hindu Other Backward Castes	0.38	0.49
Hindu Scheduled Castes	0.24	0.43
Scheduled Tribes or Indigenous	0.09	0.29
Muslim	0.13	0.34
Other	0.01	0.09
Socioeconomic status[g]		
Income quintiles		
Poorest quintile	0.25	0.43
Second quintile	0.26	0.44
Third quintile	0.21	0.41
Fourth quintile	0.15	0.36
Richest quintile	0.12	0.32
Agriculture main income source	0.57	0.50
Mother's education (grades)	3.22	4.03
Father's education (grades)	5.15	4.51

Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and NCAER 2019).

Note: N = 7,284. The sample includes only rural children. All statistics are using attrition weights constructed based on propensity score reweighting.

[a] Math skills based on children's performance on math assessment test: 1 = cannot recognize numbers, 2 = able to recognize numbers, 3 = do subtraction, 4 = do division.

[b] Reading skills based on children's performance on reading assessment test: 1 = cannot recognize letters in the alphabet, 2 = recognize letters in the alphabet, 3 = read words, 4 = read paragraphs, 5 = read stories.

[c] Grade-for-age grade / age six, where grade and age are current grade and age of the child.

[d] Village flood exposure: 0 = no flood, 1 = one or more episodes of floods between 2006 and 2011.

[e] State flood index refers to the fraction of total villages in a state exposed to one or more episodes of floods between 2006 and 2011.

[f] Female: 0 = male, 1 = female.

[g] Unequal distribution of income quintiles is because quintiles are generated at the household level based on household total income.

Table 2. Percentage Flood Exposed by Background Characteristics

	Percentage	Number in category	Flood-group independence test (χ^2)
Gender			n.s.
Male	32.6	3,873	
Female	34.0	3,411	
Child's age (years)			n.s.
Eight	34.9	1,714	
Nine	32.2	1,739	
Ten	33.4	2,233	
Eleven	32.3	1,598	
Caste-religion			***
Hindu Upper Castes	30.1	1,156	
Hindu Other Backward Castes	36.1	2,603	
Hindu Scheduled Castes	34.4	1,805	
Scheduled Tribes or Indigenous	22.1	725	
Muslim	35.3	905	
Other	11.7	90	
Income quintiles			***
Poorest quintile	38.8	1,733	
Second quintile	35.5	1,852	
Third quintile	32.9	1,524	
Fourth quintile	27.6	1,188	
Richest quintile	24.3	987	
Main income source			***
Nonagriculture	31.9	3,107	
Agriculture	34.3	4,177	
Mother's education			***
None	36.0	3,771	
Primary	31.3	1,380	
Middle or secondary	28.1	1,771	
High school or more	34.8	362	
Father's education			***
None	36.4	1,953	
Primary	35.9	1,875	
Middle or secondary	28.0	2,559	
High school or more	33.3	897	

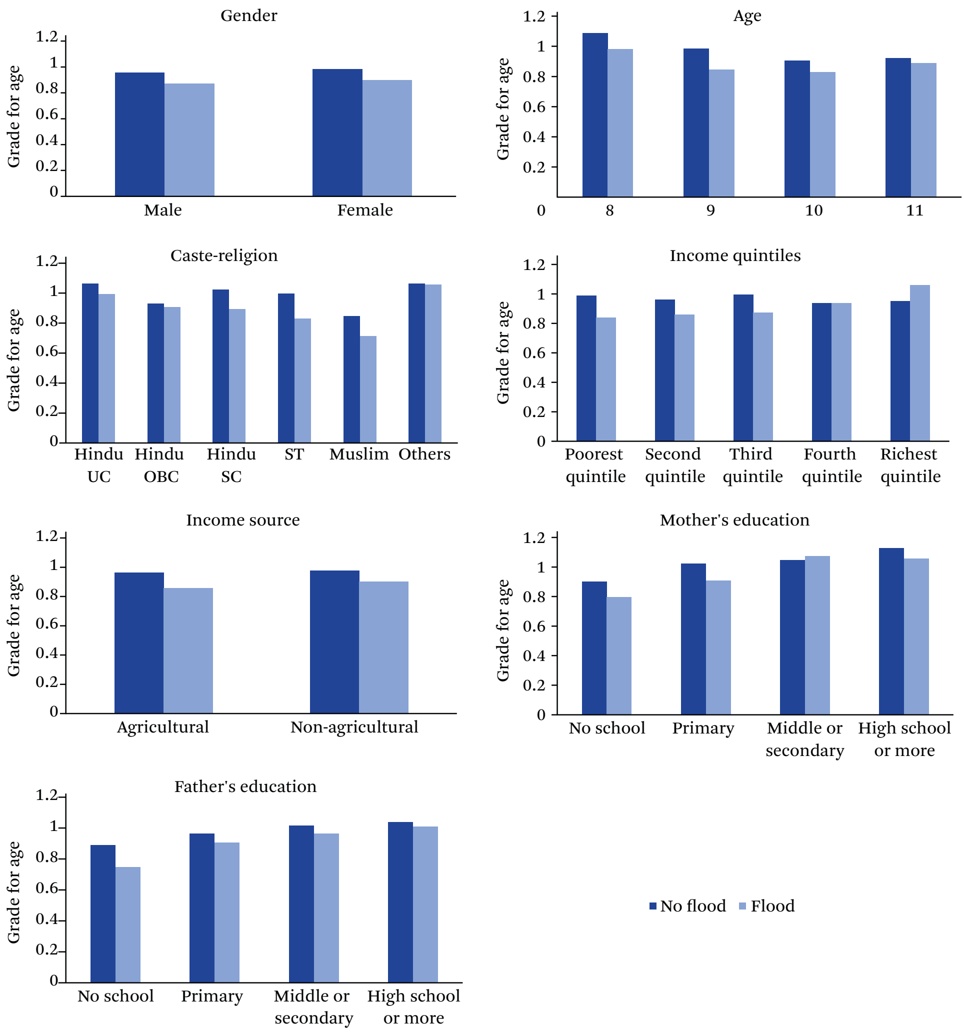
Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and NCAER 2019).
+ $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$

Educational Outcomes by Exposure and Group

Figures 1 through 3 show distributions of means of the outcome measures by background characteristics. For children's grade-for-age (figure 1), children from villages not exposed to floods tend to have positive and greater means relative to those from flood-exposed villages across various background characteristics. With the exception of girls, children from all marginalized groups, including those from agricultural households, are likely to have worse grade progression than privileged groups. Children from agricultural households are better off relative to nonagricultural households, perhaps in part because the latter group includes nonagricultural daily wage earners.

For children's math and reading skills (fig-

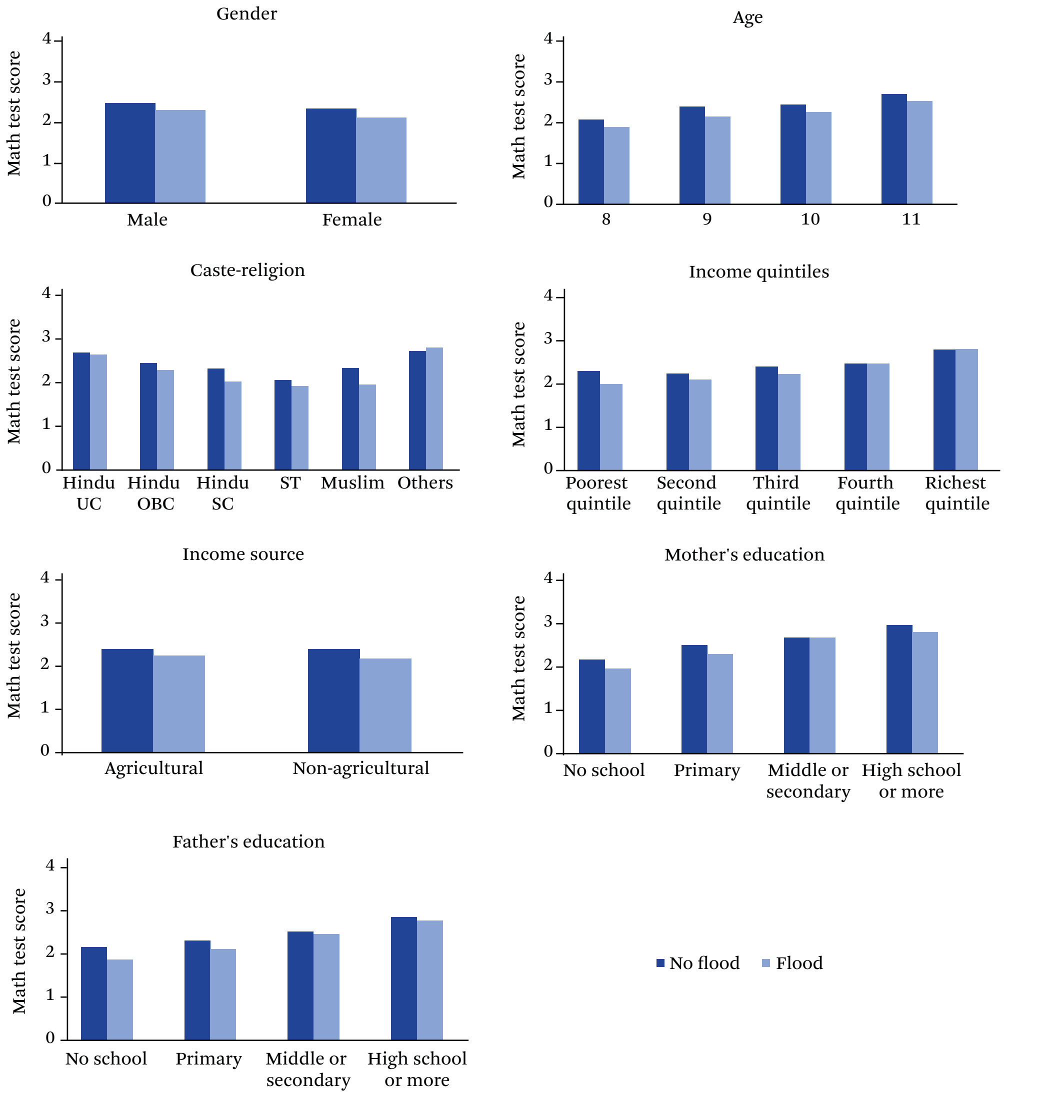
Figure 1. Distribution of Grade-for-Age by Variables Used in Regression Analysis



Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and NCAER 2019).

Note: Two sample t-tests for equality of means between grade-for-age and categories of variables in the x-axis are statistically significant at 5 percent for all except Hindu OBC and Other in caste-religion; the fourth and richest quintiles; mothers with middle or secondary and high school or more; and fathers with high school or more.

Figure 2. Distribution of Math Skills by Variables Used in Regression Analysis

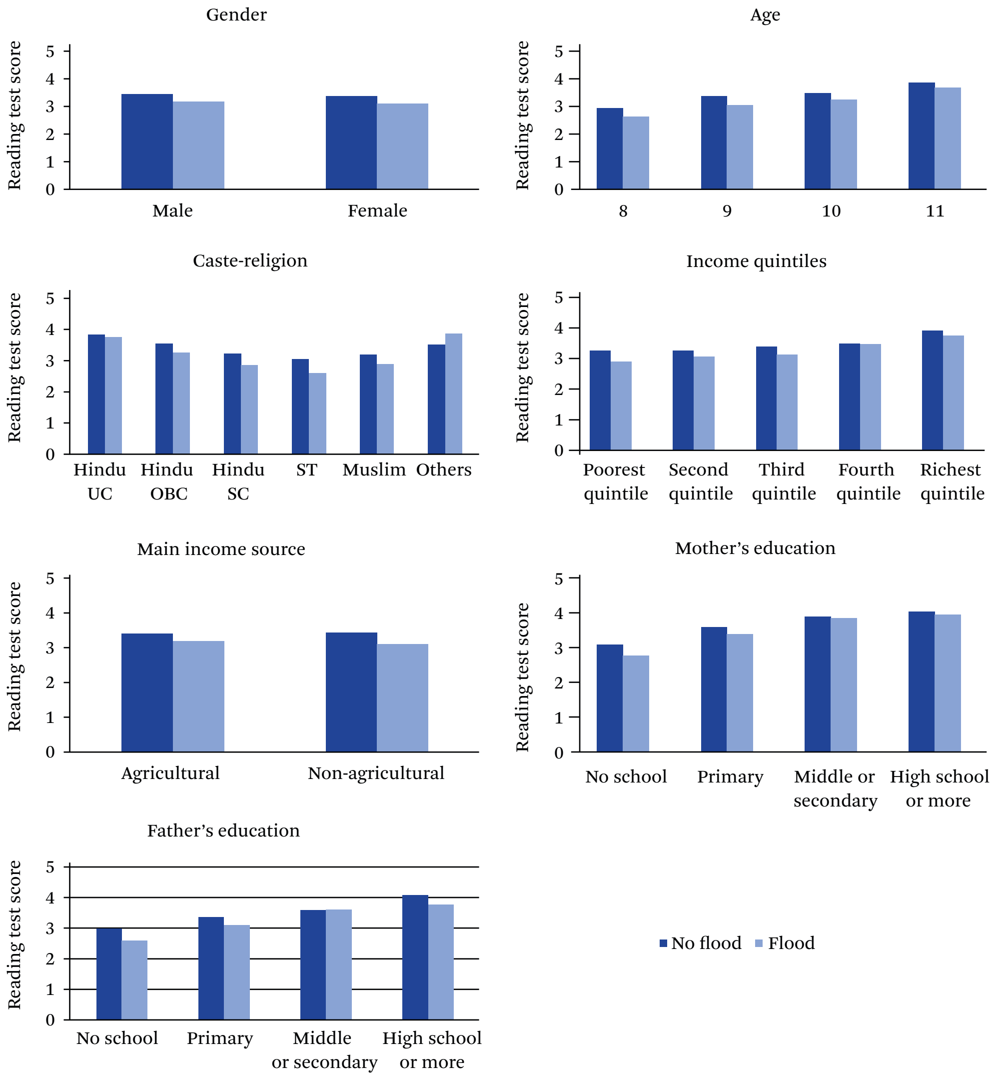


Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and NCAER 2019).

Note: Two sample t-tests for equality of means between math skills and categories of variables in the x-axis are statistically significant at 5 percent for all except Other in caste-religion; the third, fourth, and richest quintiles; mothers with primary education; and fathers with high school or more.

ures 2 and 3), children from flood-exposed villages have lower mean skills than those in villages not exposed. Scores increase with age. Girls (in the case of math) and children belonging to marginalized caste or religious groups have worse skills relative to less-marginalized children in their respective groups. Higher income quintiles and higher parental education are associated with higher skills. Even within villages exposed to floods, higher parental education is associated with higher skills.

Figure 3. Distribution of Reading Skills by Variables Used in Regression Models



Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and NCAER 2019).

Note: Two sample t-test for equality of means between reading skills and categories of variables in the x-axis are statistically significant at 5 percent for all except Other in caste-religion; the third, fourth, and richest quintiles; mothers with primary education; fathers with middle or secondary schooling.

OLS Analyses of Grade-for-Age

The first model in table 3 shows the main effects. The coefficient estimates for village flood exposure and state flood index are both negative (though the former is significant only at the 0.10 level), suggesting that children in flood-exposed areas fall behind. Girls perform better than boys, and older children are further behind than younger children. Muslim, Hindu Other Backward Caste, and Scheduled Tribe or Indigenous children are significantly behind relative to Hindu Upper Caste children. However, it is puzzling that children from the two highest income quintiles households are behind relative to those from the poorest quintile. A possible explanation for this could be that such children start later by their parents' choice, or that they attend higher-quality and more-demanding schools in which grade promotion is less automatic. Higher parental education, about twice as much for mothers as for fathers, is associated with higher grade attainment for age. The second and third columns present estimates with, in addition to the main effects, interactions between village flood exposure and other main-effects-model variables. In addition, the third column has village fixed effects and is our preferred model. We focus here on the significant estimates of the coefficients of the interactions, which indicate how the associations with village floods differ from the overall average effects for the background characteristics interacted with the village flood variable.[2] The patterns of the estimates of interactions are similar between columns 2 and 3 with the exceptions that agricultural households have a significantly positive coefficient and Hindu Other Backward Castes have a negative coefficient in column 2, which are no longer significant in column 3 with the control for village fixed effects. After accounting for the fixed village-level characteristics in column 3, a positive coefficient estimate of household income suggests that richer children are better able to moderate the negative association between flood exposure and grade-for-age in comparison with children from lowest income quintile. Our model also finds that mothers with more education can significantly moderate probabilities of children falling behind with flood exposure relative to those with less education.

OLS Analysis of Academic Skills

Table 4 presents estimates for age-standardized math skills as the dependent variable to facilitate interpretation. The main-effects model (column 1) shows a statistically significant negative association of –0.141 SD between village flood exposure and math, holding constant all other sociodemographic variables in the model. Although negative, the coefficient estimate for the state-flooding index is not significantly associated with math performance. Girls (–0.138 SD) and children from Hindu Scheduled Castes (–0.141 SD), Scheduled Tribes and Indigenous (ST) (–0.329 SD), and Muslims (–0.177 SD) perform significantly worse in math relative to the reference groups (that is, boys and children from Hindu Upper Castes). Children from richer households perform better than those from the poorest. Children whose parents have more education rank higher in math. The coefficient estimate for households where agriculture is the main source of household income, although negative, is not statistically significant. Among the significant effects, the largest in absolute values are for Scheduled Tribe and Indigenous children, highest income quintile children, Muslim children, and Hindu Scheduled Caste children, indicating that these characteristics are more important predictors than gender, parental education, and differences in the lower income quintiles.

Column 2 shows coefficient estimates with, in addition to the main effects, interactions between village flood exposure and each of the main-effects-model variables. The significant coefficient estimates for the interaction terms suggest that Muslim children are more vulnerable to the negative influence of flood exposure on math than children from Hindu Upper Caste households, and that richer households may also be more able to protect learning among their children in the event of flood exposure.

In the village-fixed-effect regression estimates (column 3), the coefficient estimates for the interactions with the highest two income quintiles continue to be positive (implying a protective effect of approximately a third of a standard deviation for being in the fourth rather than the first quintile, with the fifth quintile estimate not significantly different from the fourth).[3] The coefficient estimate for

2. Once the interactions are included, the coefficient estimates of the main-effect variables refer to the overall reference category (that is, boys, Hindu Upper Caste, poorest income quintile, main income source nonagriculture, and so on), which is not of particular interest for this article, so we do not discuss these estimates extensively given space constraints.

3. The *p*-value for a t-test of difference in coefficients is .148.

Table 3. Coefficient Estimates from OLS Regression of Grade-for-Age

	(1) Main Effects	(2) Flood Interactions	(3) Village Fixed Effects (Preferred)
Main effects			
Flood exposure			
Village flood exposure (ref.: no floods)	−0.022+	−0.423***	
	(0.011)	(0.110)	
State flooding index	−0.455***	−0.469***	
	(0.032)	(0.038)	
Demographic characteristics			
Female (ref.: male)	0.029**	0.025*	0.028*
	(0.010)	(0.012)	(0.012)
Age	−0.055***	−0.062***	−0.062***
	(0.005)	(0.006)	(0.006)
Caste-religion (ref.: Hindu Upper Castes)			
Hindu Other Backward Castes	−0.066***	−0.099***	−0.039
	(0.016)	(0.019)	(0.024)
Hindu Scheduled Castes	−0.004	−0.011	−0.059*
	(0.018)	(0.021)	(0.025)
Scheduled Tribes or Indigenous	−0.052*	−0.052*	−0.095**
	(0.022)	(0.025)	(0.036)
Muslim	−0.179***	−0.185***	−0.130***
	(0.02)	(0.024)	(0.035)
Other	−0.049	−0.051	−0.181*
	(0.059)	(0.063)	(0.089)
Socioeconomic status			
Income quintiles (ref.: poorest quintile)			
Second quintile	−0.015	−0.030+	−0.056**
	(0.014)	(0.018)	(0.018)
Third quintile	−0.018	−0.026	−0.032+
	(0.015)	(0.018)	(0.020)
Fourth quintile	−0.057***	−0.089***	−0.058**
	(0.017)	(0.020)	(0.022)
Richest quintile	−0.080***	−0.138***	−0.086***
	(0.019)	(0.023)	(0.026)
Agricultural household (ref.: non-agricultural household)	0.013	0.001	−0.013
	(0.01)	(0.013)	(0.015)
Mother's education (grades)	0.016***	0.014***	0.005*
	(0.002)	(0.002)	(0.002)
Father's education (grades)	0.008***	0.008***	0.008***
	(0.001)	(0.002)	(0.002)
Village flood interactions			
Flood exposure			
State flooding index		0.071	
		(0.071)	
Demographic characteristics			
Female		0.009	−0.018
		(0.021)	(0.021)
Age		0.024*	0.014
		(0.010)	(0.010)

(continued)

Table 3. (*continued*)

	(1) Main Effects	(2) Flood Interactions	(3) Village Fixed Effects (Preferred)
Caste-religion			
Hindu Other Backward Castes		0.103**	0.061
		(0.034)	(0.041)
Hindu Scheduled Castes		0.032	0.073
		(0.038)	(0.045)
Scheduled Tribes or Indigenous		−0.024	0.091
		(0.051)	(0.071)
Muslim		0.029	−0.015
		(0.043)	(0.058)
Other		0.024	0.094
		(0.181)	(0.220)
Socioeconomic status			
Income quintiles			
Second quintile		0.037	0.089**
		(0.029)	(0.03)
Third quintile		0.018	−0.002
		(0.031)	(0.033)
Fourth quintile		0.110**	0.074+
		(0.036)	(0.039)
Richest quintile		0.221***	0.180***
		(0.042)	(0.047)
Agricultural household		0.044*	0.031
		(0.022)	(0.025)
Mother's education (grades)		0.006+	0.008*
		(0.003)	(0.004)
Father's education (grades)		−0.001	0.002
		(0.003)	(0.003)
Constant	1.595***	1.719***	1.475***
	(0.051)	(0.061)	(0.049)
N	7,284	7,284	7,284
R^2	0.107	0.116	0.418
Akaike information criterion	8,227.780	8,185.581	5,126.425
Bayesian information criterion	8,344.968	8,406.171	5,326.334

Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and NCAER 2019).

Note: Standard errors in the second row. Coefficients are weighted using attrition weights calculated based on response propensities.

+ $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$

Muslim, however, is no longer statistically significant, even though the magnitude of the estimate is not changed substantially from that in column 2, because the precision of this estimate declines with the village fixed effects. The interaction coefficient on flood exposure and gender is significantly negative for girls with controls for village fixed effects (protective effect for boys of about a tenth of a standard deviation). In regard to interactions with the flood

Table 4. Coefficient Estimates from OLS Regression of Age-Standardized Math Skills

	(1) Main Effects	(2) Flood Interactions	(3) Village Fixed Effects (Preferred)	(4) Flood Interactions + Grade-for-Age
Main Effects				
Flood exposure				
Village flood exposure (ref.: no floods)	−0.141***	−0.197		0.105
	(0.025)	(0.239)		(0.242)
State flooding index	−0.086	0.001	0.000	0.274***
	(0.070)	(0.083)	(.)	(0.081)
Demographic characteristics				
Female (ref.: male)	−0.138***	−0.119***	−0.115***	−0.134***
	(0.022)	(0.026)	(0.027)	(0.026)
Age	−0.004	−0.007	−0.006	0.030*
	(0.010)	(0.012)	(0.012)	(0.012)
Caste-religion (ref.: Hindu Upper Castes)				
Hindu Other Backward Castes	−0.024	−0.022	−0.054	0.036
	(0.035)	(0.042)	(0.053)	(0.040)
Hindu Scheduled Castes	−0.141***	−0.103*	−0.246***	−0.097*
	(0.038)	(0.046)	(0.056)	(0.044)
Scheduled tribes or Indigenous	−0.329***	−0.333***	−0.331***	−0.303***
	(0.048)	(0.055)	(0.080)	(0.053)
Muslim	−0.177***	−0.105*	−0.017	0.003
	(0.043)	(0.052)	(0.078)	(0.051)
Other	0.029	0.045	−0.320	0.074
	(0.127)	(0.136)	(0.196)	(0.132)
Socioeconomic status				
Income quintiles (ref.: poorest quintile)				
Second quintile	0.011	−0.052	−0.093*	−0.034
	(0.030)	(0.038)	(0.041)	(0.037)
Third quintile	0.084**	0.037	−0.014	0.052
	(0.032)	(0.040)	(0.043)	(0.038)
Fourth quintile	0.117**	0.020	−0.093+	0.071+
	(0.036)	(0.043)	(0.050)	(0.042)
Richest quintile	0.290***	0.224***	0.043	0.305***
	(0.041)	(0.049)	(0.057)	(0.047)
Agricultural household (ref.: non-agricultural household)	−0.032	−0.012	0.056+	−0.013
	(0.022)	(0.027)	(0.033)	(0.026)
Mother's education (grades)	0.044***	0.042***	0.042***	0.034***
	(0.003)	(0.004)	(0.005)	(0.004)
Father's education (grades)	0.027***	0.025***	0.023***	0.020***
	(0.003)	(0.004)	(0.004)	(0.003)
Educational progress				
Grade-for-age				0.583***
				(0.030)
Village flood interactions				
Flood exposure				
State flood index		−0.215		−0.274+
		(0.155)		(0.151)

(continued)

Table 4. (*continued*)

	(1) Main Effects	(2) Flood Interactions	(3) Village Fixed Effects (Preferred)	(4) Flood Interactions + Grade-for-Age
Demographic characteristics				
Female		−0.056	−0.111*	−0.060
		(0.046)	(0.046)	(0.044)
Age		0.010	−0.011	−0.006
		(0.021)	(0.021)	(0.021)
Caste-religion				
Hindu Other Backward Castes		−0.014	0.072	−0.074
		(0.074)	(0.089)	(0.072)
Hindu Scheduled Castes		−0.108	0.034	−0.126
		(0.082)	(0.099)	(0.079)
Scheduled Tribes or Indigenous		0.036	0.033	0.046
		(0.111)	(0.157)	(0.107)
Muslim		−0.190*	−0.201	−0.214*
		(0.093)	(0.127)	(0.090)
Other		−0.007	0.242	−0.022
		(0.391)	(0.485)	(0.377)
Socioeconomic status				
Income quintiles				
Second quintile		0.149*	0.106	0.128*
		(0.063)	(0.066)	(0.060)
Third quintile		0.107	0.043	0.096
		(0.067)	(0.073)	(0.065)
Fourth quintile		0.296***	0.343***	0.233**
		(0.077)	(0.086)	(0.075)
Richest quintile		0.196*	0.187+	0.071
		(0.092)	(0.103)	(0.089)
Agricultural household		−0.055	−0.093+	−0.078+
		(0.048)	(0.056)	(0.046)
Mother's education (grades)		0.004	−0.004	0.001
		(0.007)	(0.008)	(0.007)
Father's education (grades)		0.006	0.007	0.007
		(0.006)	(0.007)	(0.006)
Educational progress				
Grade-for-age				−0.044
				(0.052)
Constant	−0.117	−0.088	−0.052	−1.090***
	(0.109)	(0.132)	(0.108)	(0.138)
N	7,284	7,284	7,284	7,284
R^2	0.136	0.141	0.414	0.200
Akaike information criterion	19,459.460	19,448.510	16,651.847	18,933.109
Bayesian information criterion	19,576.648	19,669.100	16,851.757	19,167.486

Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and NCAER 2019).

Note: Standard errors in parentheses. Coefficients are weighted using attrition weights calculated based on test response propensities.

$^+$ $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$

exposure variable, the other Hindu categories are not significantly disadvantaged relative to Hindu Upper Castes and parental education does not have significant coefficient estimates in any of the three sets of interaction estimates. Overall, our results indicate that even though children face marginalization of various forms, the economic resources of their households are likely to help them overcome loss in mathematical achievement in villages when floods occur. Furthermore, boys' math achievement is affected less than girls.

Finally, column 4 includes main effects, interactions, and grade-for-age (and its interaction with village flood exposure) to control for a possible mechanism through which floods might affect learning. The coefficient estimate on grade-for-age is not significantly nonzero, suggesting that this is not an important mechanism for math, so we do not discuss the other coefficient estimates here.

Table 5 presents estimates for age-standardized reading skills as the dependent variable. The estimates generally follow similar patterns to those for math skills in table 4. The only difference for the basic main-effects model (column 1) is the significantly negative coefficient estimate (–0.255 SD) for the state flood index for reading, in addition to the significantly negative estimate for village flood exposure (–0.118 SD). When interactions are added (column 2), for reading but not for math, the significant negative interaction between the village and the state flood variables indicates greater negative effects of village floods in states in which floods are more prevalent. For reading, the coefficient estimate for interactions of village floods is negative and marginally significant for Scheduled Tribes but not for Muslims. This contrasts with the coefficient estimate for math, which is negative and significant only for Muslims. Column 3 presents village fixed effects coefficient estimates. Unlike in math skills, the economic resources of children's households and child's gender do not seem to have significant protective effects against loss in reading achievement in villages when floods occur. When the grade-for-age variable is added (column 4), one difference for reading versus math is that for reading the grade-for-age variable is marginally significantly negative, consistent with grade-for-age possibly being one mechanism though which floods affect learning. Most of the other estimates are similar to those for the interactions model (column 2) except that interactions with Other Backward Castes and the richest quintile have marginally significant negative coefficient estimates, the latter of which is puzzling.

DISCUSSION AND CONCLUSIONS

Climate change is a growing global concern. One manifestation is increased flooding, particularly in LMICs in which protective measures for flooding are often limited, but also in high-income countries such as the United States. Relatively little is known, however, about the relations between flooding in LMICs and children's education, though a priori it would seem that important negative effects due to flood impacts on school infrastructures, access to schools, and time used for children's learning are possible. Moreover, such effects may be relatively large for marginalized children as identified by gender, caste, religion, and socioeconomic status.

This article contributes to the limited literature by characterizing differential exposure to floods for different marginalized groups and estimating empirical relations between flood exposure and educational outcomes for children in rural areas in India, a country that has substantial and increasing flood exposure and has the world's largest population of school-age children. Our emphasis is not on school enrollments and educational attainment, as in much of the literature on education in LMICs. Instead, we focus on timely progress and what children actually know about basic math and reading—whether or not they were in school at the time of the surveys. This approach is an improvement on studies that are limited to children in school, which is likely to be a selected subpopulation.

This article highlights the importance of distinguishing differential exposures and differential impacts in analyzing social stratification in the experience of disruption in childhood. The characterization of differential exposure to floods for different marginalized groups shows that differences are significant—by caste or religious group, with marginalized

Table 5. Coefficient Estimates from OLS Regression of Age-Standardized Reading Skills

	(1) Main Effects	(2) Flood Interactions	(3) Village Fixed Effects (Preferred)	(4) Flood Interactions + Grade-for-Age
Main effects				
Flood exposure				
Village flood exposure (ref.: no floods)	−0.118***	−0.133		−0.023
	(0.025)	(0.244)		(0.248)
State flood index	−0.255***	−0.110	0.000	0.143+
	(0.071)	(0.085)	(.)	(0.083)
Demographic characteristics				
Female (ref.: male)	−0.031	−0.028	−0.028	−0.042
	(0.022)	(0.027)	(0.028)	(0.026)
Age	−0.005	−0.012	0.003	0.022+
	(0.010)	(0.013)	(0.013)	(0.012)
Caste-religion (ref.: Hindu Upper Castes)				
Hindu Other Backward Castes	−0.006	0.019	−0.060	0.072+
	(0.035)	(0.043)	(0.054)	(0.041)
Hindu Scheduled Castes	−0.212***	−0.185***	−0.283***	−0.179***
	(0.039)	(0.047)	(0.057)	(0.045)
Scheduled tribe or Indigenous	−0.307***	−0.257***	−0.287***	−0.229***
	(0.049)	(0.056)	(0.082)	(0.055)
Muslim	−0.219***	−0.208***	−0.098	−0.108*
	(0.044)	(0.054)	(0.080)	(0.052)
Other	−0.221+	−0.224	−0.551**	−0.197
	(0.130)	(0.139)	(0.201)	(0.135)
Socioeconomic status				
Income quintiles (ref.: poorest quintile)				
Second quintile	0.051	0.007	0.003	0.023
	(0.031)	(0.039)	(0.042)	(0.037)
Third quintile	0.045	0.028	0.033	0.042
	(0.033)	(0.041)	(0.044)	(0.039)
Fourth quintile	0.066+	0.002	−0.033	0.050
	(0.036)	(0.044)	(0.051)	(0.043)
Richest quintile	0.162***	0.162**	0.101+	0.237***
	(0.042)	(0.050)	(0.058)	(0.048)
Agricultural household (ref.: non-agricultural household)	−0.034	−0.019	0.060+	−0.020
	(0.023)	(0.028)	(0.034)	(0.027)
Mother's education (grades)	0.043***	0.040***	0.035***	0.032***
	(0.003)	(0.004)	(0.005)	(0.004)
Father's education (grades)	0.029***	0.028***	0.024***	0.024***
	(0.003)	(0.004)	(0.004)	(0.004)
Educational progress				
Grade-for-age				0.540***
				(0.031)
Village flood interactions				
Flood exposure				
State flood index		−0.509**		−0.511***
		(0.158)		(0.155)

Table 5. (*continued*)

	(1) Main Effects	(2) Flood Interactions	(3) Village Fixed Effects (Preferred)	(4) Flood Interactions + Grade-for-Age
Demographic characteristics				
Female		−0.002	−0.082+	−0.010
		(0.047)	(0.047)	(0.045)
Age		0.022	−0.027	0.013
		(0.022)	(0.022)	(0.021)
Caste-religion				
Hindu Other Backward Castes		−0.074	0.042	−0.130+
		(0.076)	(0.092)	(0.074)
Hindu Scheduled Castes		−0.075	0.052	−0.094
		(0.084)	(0.101)	(0.081)
Scheduled Tribe or Indigenous		−0.211+	−0.185	−0.192+
		(0.114)	(0.161)	(0.110)
Muslim		−0.018	−0.069	−0.020
		(0.095)	(0.130)	(0.092)
Other		0.169	0.355	0.159
		(0.400)	(0.498)	(0.386)
Socioeconomic status				
Income quintiles				
Second quintile		0.105	0.063	0.084
		(0.064)	(0.068)	(0.062)
Third quintile		0.029	−0.096	0.020
		(0.069)	(0.075)	(0.066)
Fourth quintile		0.193*	0.147+	0.132+
		(0.079)	(0.088)	(0.076)
Richest quintile		−0.035	0.019	−0.162+
		(0.094)	(0.106)	(0.091)
Agricultural household		−0.048	−0.080	−0.076
		(0.049)	(0.057)	(0.047)
Mother's education (grades)		0.010	0.008	0.005
		(0.007)	(0.008)	(0.007)
Father's education (grades)		0.002	0.008	0.003
		(0.007)	(0.007)	(0.006)
Educational progress				
Grade-for-age				0.090+
				(0.053)
Constant	−0.083	−0.053	−0.148	−0.981***
	(0.112)	(0.135)	(0.111)	(0.141)
N	7,284	7,284	7,284	7,284
R^2	0.121	0.125	0.398	0.184
Akaike information criterion	19,772.461	19,769.331	17,039.803	19,270.257
Bayesian information criterion	19,889.649	19,989.921	17,239.713	19,504.634

Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and NCAER 2019).
Note: Standard errors in parentheses. Coefficients are weighted using attrition weights calculated based on test response propensities.
+ $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$

Hindu castes and Muslims more exposed; by socioeconomic status, with children from poorer households with parents with less education more exposed; and by major income source, with agricultural households somewhat more exposed. In short, we show substantial evidence of differential exposures across many of the key stratifiers in Indian society. Findings demonstrate a lack of significant differences in exposure by gender or age.

In contrast, the estimation of effect heterogeneity of flood exposure tells a slightly different story. Our preferred village fixed-effects specifications finds the following three significant (in some cases marginally significant) flood-social group interactions: flood effects on increasing grade-for-age are greater for poorer income quintiles; flood effects reduce math skills more for girls and poorer households; and flood effects reduce reading skills more for girls but the fourth income quintile is protective. In these estimates for the three educational outcomes, age, caste-religion, agricultural main income source, and parental education do not significantly interact with flood exposure. Overall, the number of interactions is limited and many of the significant ones are not very large in magnitude. In short, although marginalized children are disproportionately likely to experience floods, relative to other rural children, systematic evidence is less of disproportionate educational penalties relative to the penalties other children face when floods do occur. In other estimates, we investigate the possibility that grade-for-age is a mechanism for the impacts of floods on learning, but only find marginally significant coefficient estimates for reading and not for math.

This study has limitations. The data used permit estimates of associations, not of causal effects.[4] Flood exposure may be operating as a proxy, in part for a constellation of other associated factors that make some children more vulnerable, though we control for a number of observed variables and, in our preferred estimates, for unobserved village characteristics. Moreover, the outcome variables pertain only to grade-for-age and to fairly limited categorical indicators of basic mathematics and reading, not to more nuanced learning or to more advanced learning. Finally, it is important to acknowledge that these findings likely underrepresent the scale of disparities across all children in India, because urban children as a group enjoy educational and economic advantages and our sample focuses on disparities within the rural population.

Nevertheless, this study contributes to a very limited literature about flood exposure and education by analyzing the case of India—a LMIC with the largest population of school-age children in the world. Findings suggest the need to better understand the impacts of flooding on educational outcomes among marginalized populations in other LMICs as well as in high-income countries (Azevedo et al. 2021; EPA 2021; Lieberman-Cribbin et al. 2021). Findings also highlight the need for further efforts to identify causal relations and mitigating factors. One policy implication is that effective strategies need to be designed, piloted, and implemented to minimize disproportionate exposure and its adverse educational outcomes for marginalized children—both in LMICs such as India and in high-income countries (EPA 2021; Kousky 2016; World Bank 2019). The effectiveness of such strategies in LMICs could have important implications for the composition—that is, development versus disaster relief—and the amount of aid flows from high-income countries and international organizations to LMICs.

REFERENCES

Ali, Haider, Parth Modi, and Vimal Mishra. 2019. "Increased Flood Risk in Indian Sub-Continent under the Warming Climate." *Weather and Climate Extremes* 25 (September): 1–9. DOI: https://doi.org/10.1016/j.wace.2019.100212.

Aquino, Taylor, Jennie E. Brand, and Florencia Torche. 2022. "Unequal Effects of Disruptive Events." *Sociology Compass* 16(4): e12972. DOI: https://doi.org/10.1111/soc4.12972.

Arcaya, Mariana, Ethan J. Raker, and Mary C. Waters. 2020. "The Social Consequences of Disas-

4. Taylor Aquino, Jennie Brand, and Florencia Torche (2022) and Torche, Jason Fletcher, and Brand (2024, this issue) address concerns related to causal interpretation under disruptive events, broadly defined, and also provide methodological insights on how to pursue causal interpretation under certain conditions.

ters: Individual and Community Change." *Annual Review of Sociology* 46(1): 671–91. DOI: https://doi.org/10.1146/annurev-soc-121919-054827.

Asher, Sam, Paul Novosad, and Charlie Rafkin. 2018. "Intergenerational Mobility in India: Estimates from New Methods and Administrative Data." Working Paper no. 560. Washington, D.C.: World Bank. Accessed June 30, 2023. http://barrett.dyson.cornell.edu/NEUDC/paper_560.pdf.

Azevedo, João Pedro, Amer Hasan, Diana Goldemberg, Koen Geven, and Syedah Aroob Iqbal. 2021. "Simulating the Potential Impacts of COVID-19 School Closures on Schooling and Learning Outcomes: A Set of Global Estimates." *World Bank Research Observer* 36(1): 1–40. DOI: https://doi.org/10.1093/wbro/lkab003.

Baez, Javier, Alejandro de la Fuente, and Indhira Vanessa Santos. 2010. "Do Natural Disasters Affect Human Capital? An Assessment Based on Existing Empirical Evidence." *IZA* discussion paper no. 5164. Bonn: Institute of Labor Economics. DOI: https://doi.org/10.2139/ssrn.1672172.

Bahinipati, Chandra Sekhar, and Unmesh Patnaik. 2020. "Does Development Reduce Damage Risk from Climate Extremes? Empirical Evidence for Floods in India." *Water Policy* 22(5): 748–67. DOI: https://doi.org/10.2166/wp.2020.059.

Benson, Charlotte, and Edward J. Clay. 2004. *Understanding the Economic and Financial Impacts of Natural Disasters*. Washington, D.C.: World Bank.

Bertho, Anna, Devyani Pande, Pankaj Shrichand, Shikha Singh, and Purvanchal Grameen Vikas Sansthan. 2012. "Impact of Disasters on Children in UP and Bihar." KCCI/2012-03. New Delhi: Knowledge Community on Children in India. Accessed June 30, 2023. https://www.academia.edu/4516554/03_Impact_of_Disasters_on_Children_in_UP_and_Bihar.

Brusi, Rima, and Isar Godreau. 2019. "Dismantling Public Education in Puerto Rico." In *Aftershocks of Disaster: Puerto Rico Before and After the Storm*, edited by Yarimar Bonilla and Marisol LéBrón. Chicago: Haymarket Books.

Carty, Tracy, and Lyndsay Walsh. 2022. "Footing the Bill: Fair Finance for Loss and Damage in an Era of Escalating Climate Impacts." Briefing Paper. Oxford: Oxfam International. DOI: https://doi.org/10.21201/2022.8977.

Chakrabarti, Rajashri, and Max Livingston. 2012. "The Impact of Superstorm Sandy on New York City School Closures and Attendance." New York: Federal Reserve Bank.

Chen, Qixuan, Andrew Gelman, Melissa Tracy, Fran H. Norris, and Sandro Galea. 2015. "Incorporating the Sampling Design in Weighting Adjustments for Panel Attrition." *Statistics in Medicine* 34(28): 3637–47. DOI: https://doi.org/10.1002/sim.6618.

Coffey, Diane, Angus Deaton, Jean Drèze, Dean Spears, and Alessandro Tarozzi. 2013. "Stunting Among Children: Facts and Implications." *Economic and Political Weekly* 48(34): 68–70.

Coffey, Diane, Payal Hathi, Nidhi Khurana, and Amit Thorat. 2018. "Explicit Prejudice." *Economic & Political Weekly* 53(1): 47.

Currie, Janet, and Tom Vogl. 2013. "Early-Life Health and Adult Circumstance in Developing Countries." *Annual Review of Economics* 5(1): 1–36. DOI: https://doi.org/10.1146/annurev-economics-081412-103704.

Desai, Sonalde, Amaresh Dubey, Brij Lal Joshi, Mitali Sen, Abusaleh Sharif, and Reeve Vanneman. 2010. *Human Development in India: Challenges for a Society in Transition*. *OUP Catalogue*. New Delhi: Oxford University Press. Accessed June 30, 2023. https://ideas.repec.org/b/oxp/obooks/9780198065128.html.

Desai, Sonalde, and Veena Kulkarni. 2008. "Changing Educational Inequalities in India in the Context of Affirmative Action." *Demography* 45(2): 245–70. DOI: https://doi.org/10.1353/dem.0.0001.

Desai, Sonalde, Reeve Vanneman, and National Council of Applied Economic Research (NCAER). 2019. "India Human Development Survey Panel (IHDS, IHDS-II), 2005, 2011–2012: Version 1." Interuniversity Consortium for Political and Social Research. Accessed June 30, 2023. https://www.icpsr.umich.edu/web/DSDR/studies/37382/versions/V1.

Deshpande, Ashwini. 2011. *The Grammar of Caste: Economic Discrimination in Contemporary India*. New Delhi: Oxford University Press. DOI: https://doi.org/10.1093/acprof:oso/9780198072034.001.0001.

Dimitrova, Anna, and Raya Muttarak. 2020. "After the Floods: Differential Impacts of Rainfall Anomalies on Child Stunting in India." *Global Environmental Change* 64 (September): 102130. DOI: https://doi.org/10.1016/j.gloenvcha.2020.102130.

Duguid, Kate. 2021. "Cost of Flood Damage to U.S.

Homes Will Increase by 61% in 30 Years." Reuters, February 22. Accessed June 30, 2023. https://www.reuters.com/business/environment/cost-flood-damage-us-homes-will-increase-by-61-30-years-2021-02-22/.

Ebi, Kristie L, and Jerome A. Paulson. 2007. "Climate Change and Children." *Pediatric Clinics of North America* 54(2): 213–26.

Eckstein, David, Vera Künzel, and Laura Schäfer. 2021. "Global Climate Risk Index 2021: Who Suffers Most Extreme Weather Events? Weather-Related Loss Events in 2019 and 2000–2019." Germanwatch Nord-Süd Initiative eV, January. Accessed June 30, 2023. https://www.germanwatch.org/en/19777.

EM-DAT. 2018. "The International Disasters Database." Accessed June 30, 2023. https://emdat.be/.

———. 2021. "The International Disaster Database." Accessed June 30, 2023. https://www.emdat.be/database.

Enarson, Elaine Pitt. 2012. *Women Confronting Natural Disaster: From Vulnerability to Resilience*. Boulder, Colo.: Lynne Rienner.

Fazal, Tanweer. 2020. *The Minority Conundrum: Living in Majoritarian Times*. New Delhi: Penguin Random House.

Frankenberg, Elizabeth, Jed Friedman, Thomas Gillespie, Nicholas Ingwersen, Robert Pynoos, Iip Umar Rifai, Bondan Sikoki, Alan Steinberg, Cecep Sumantri, and Wayan Suriastini. 2008. "Mental Health in Sumatra after the Tsunami." *American Journal of Public Health* 98(9): 1671–77.

Frankenberg, Elizabeth, Maria Laurito, and Duncan Thomas. 2014. "The Demography of Disasters." In *International Encyclopedia of the Social and Behavioral Sciences*, 2nd ed., edited by James D. Wright. Amsterdam: North Holland.

Frankenberg, Elizabeth, Bondan Sikoki, Cecep Sumantri, Wayan Suriastini, and Duncan Thomas. 2013. "Education, Vulnerability, and Resilience After a Natural Disaster." *Ecology and Society: A Journal of Integrative Science for Resilience and Sustainability* 18(2): 16. Accessed June 30, 2023. https://pubmed.ncbi.nlm.nih.gov/25170339/.

Frankenberg, Elizabeth, and Duncan Thomas. 2017. "Human Capital and Shocks: Evidence on Education, Health, and Nutrition." In *The Economics of Poverty Traps*, edited by Christopher B. Barrett, Michael R. Carter, and Jean-Paul Chavas. Chicago: University of Chicago Press.

Grimm, Michael. 2020. "Michael Grimm Testimony to Committee on Science, Space and Technology." February 2. Washington: Federal Emergency Management Agency. Accessed June 30, 2023. https://www.fema.gov/fact-sheet/michael-grimm-testimony-committee-science-space-and-technology.

Harbeson, John, and Keith McCormick. 2021. "The Impact of Climate Change on U.S. Foreign Policy and the National Interest." *American Diplomacy* (blog), May 2021. Accessed June 30, 3023. https://americandiplomacy.web.unc.edu/2021/05/the-impact-of-climate-change-on-u-s-foreign-policy/.

Hathi, Payal, Diane Coffey, Nazar Khalid, Nidhi Khurana, and Amit Thorat. 2018. "Experiences and Perceptions of Discrimination among Dalits and Muslims." *Economic & Political Weekly* 53(42): 14–17.

Hirabayashi, Yukiko, Roobavannan Mahendran, Sujan Koirala, Lisako Konoshima, Dai Yamazaki, Satoshi Watanabe, Hyungjun Kim, and Shinjiro Kanae. 2013. "Global Flood Risk under Climate Change." *Nature Climate Change* 3(9): 816–21. DOI: https://doi.org/10.1038/nclimate1911.

Jaffrelot, Christophe, and Laurent Gayer. 2012. *Muslims in Indian Cities: Trajectories of Marginalisation*. New York: Columbia University Press.

Khan, Junaid, and Sanjay K. Mohanty. 2018. "Spatial Heterogeneity and Correlates of Child Malnutrition in Districts of India." *BMC Public Health* 18(1): 1–13. DOI: https://doi.org/10.1186/s12889-018-5873-z.

Kousky, Carolyn. 2016. "Impacts of Natural Disasters on Children." *The Future of Children* 26(1): 73–92. DOI: https://doi.org/10.1353/foc.2016.0004.

Krishna, Revathi N., Kevin R. Ronan, and Eva Alisic. 2018. "Children in the 2015 South Indian Floods: Community Members' Views." *European Journal of Psychotraumatology* 9(Suppl 2): 1486122. DOI: https://doi.org/10.1080/20008198.2018.1486122.

Kumar, M. Mohan, Vineet Kumar Pathak, and Manisha Ruikar. 2020. "Tribal Population in India: A Public Health Challenge and Road to Future." *Journal of Family Medicine and Primary Care* 9(2): 508–12. DOI: https://doi.org/10.4103/jfmpc.jfmpc_992_19.

Lieberman-Cribbin, Wil, Christina Gillezeau, Rebecca M. Schwartz, and Emanuela Taioli. 2021. "Unequal Social Vulnerability to Hurricane Sandy Flood Exposure." *Journal of Exposure Science & Environmental Epidemiology* 31(5): 804–9. DOI: https://doi.org/10.1038/s41370-020-0230-6.

Maharatna, Arup. 2000. "Fertility, Mortality and Gender Bias among Tribal Population: An Indian Perspective." *Social Science & Medicine* 50(10): 1333–51.

Marchetta, Francesca, David E. Sahn, and Luca Tiberti. 2019. "The Role of Weather on Schooling and Work of Young Adults in Madagascar." *American Journal of Agricultural Economics* 101(4): 1203–27. DOI: https://doi.org/10.1093/ajae/aaz015.

Marcotte, Dave E., and Steven W. Hemelt. 2008. "Unscheduled School Closings and Student Performance." *Education Finance and Policy* 3(3): 316–38. DOI: https://doi.org/10.1162/edfp.2008.3.3.316.

Martin, Mary-Laure. 2010. "Child Participation in Disaster Risk Reduction: The Case of Flood-Affected Children in Bangladesh." *Third World Quarterly* 31(8): 1357–75.

Meng, Xin, and Robert G. Gregory. 2002. "The Impact of Interrupted Education on Subsequent Educational Attainment: A Cost of the Chinese Cultural Revolution." *Economic Development and Cultural Change* 50(4): 935–59. DOI: https://doi.org/10.1086/342761.

Norris, Fran H., Charlene K. Baker, Arthur D. Murphy, and Krzysztof Kaniasty. 2005. "Social Support Mobilization and Deterioration After Mexico's 1999 Flood: Effects of Context, Gender, and Time." *American Journal of Community Psychology* 36(1): 15–28.

Parida, Yashobanta. 2020. "Economic Impact of Floods in the Indian States." *Environment and Development Economics* 25(3): 267–90. DOI: https://doi.org/10.1017/S1355770X19000317.

Patankar, Archana. 2019. "Impacts of Natural Disasters on Households and Small Businesses in India." *Asian Development Bank Economics* working paper no. 603. Manila: Asian Development Bank. DOI: https://doi.org/10.2139/ssrn.3590902.

Patri, Prasanta, Pritee Sharma, and Suresh Kumar Patra. 2022. "Does Economic Development Reduce Disaster Damage Risk from Floods in India? Empirical Evidence Using the ZINB Model." *International Journal of Disaster Risk Reduction* 79 (September): 103163. DOI: https://doi.org/10.1016/j.ijdrr.2022.103163.

Rauscher, Emily, and Xinyan Cao. 2024. "Unequal Effects of Wildfire Exposure on Infant Health by Maternal Education, 1995–2020." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 10(1): 255–74. DOI: https://doi.org/10.7758/RSF.2024.10.1.11.

Rosales-Rueda, Maria. 2018. "The Impact of Early Life Shocks on Human Capital Formation: Evidence from El Niño Floods in Ecuador." *Journal of Health Economics* 62 (November): 13–44. DOI: https://doi.org/10.1016/j.jhealeco.2018.07.003.

Sachar, Rajindar, Saiyid Hamid, T. K. Oommen, M. A. Basith, Rakesh Basant, Akhtar Majeed, and Abusaleh Shariff. 2006. "Social, Economic and Educational Status of the Muslim Community of India." New Delhi: East Asian Bureau of Economic Research.

Sahoo, Soham. 2017. "Intra-Household Gender Disparity in School Choice: Evidence from Private Schooling in India." *Journal of Development Studies* 53(10): 1714–30. https://doi.org/10.1080/00220388.2016.1265943.

Scheuren, Jean Michael, de Waroux Polain, R. Below, and D. Guha-Sapir. 2008. "Annual Disaster Statistical Review: Numbers and Trends 2007." Brussels: Centre for Research on the Epidemiology of Disasters. Accessed June 30, 2023. https://www.cred.be/node/316.

Thamtanajit, Kawin. 2020. "The Impacts of Natural Disaster on Student Achievement: Evidence from Severe Floods in Thailand." *Journal of Developing Areas* 54(4): 129–43. DOI: https://doi.org/10.1353/jda.2020.0042.

Torche, Florencia, Jason Fletcher, and Jennie E. Brand. 2024. "Disparate Effects of Disruptive Events on Children." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 10(1): 1–30. DOI: https://doi.org/10.7758/RSF.2024.10.1.01.

U.S. Environmental Protection Agency (EPA). 2021. "Climate Change and Social Vulnerability in the United States." PA 430-R-21-003. Washington: U.S. Government Printing Office. Accessed June 30, 3023. https://www.epa.gov/cira/social-vulnerability-report.

Vaid, Divya. 2014. "Caste in Contemporary India: Flexibility and Persistence." *Annual Review of Sociology* 40(1): 391–410. DOI: https://doi.org/10.1146/annurev-soc-071913-043303.

Walker, Susan P., Theodore D. Wachs, Julie Meeks Gardner, Betsy Lozoff, Gail A. Wasserman, Ernesto Pollitt, Julie A. Carter, and International Child Development Steering Group. 2007. "Child Development: Risk Factors for Adverse Outcomes in Developing Countries." *The Lancet* 369(9556): 145–57.

White House. 2021a. "Fact Sheet: Prioritizing Climate in Foreign Policy and National Security." Press release, October 21. Washington, D.C.: The White House. Accessed June 30, 2023. https://www.whitehouse.gov/briefing-room/statements-releases/2021/10/21/fact-sheet-prioritizing-climate-in-foreign-policy-and-national-security/.

———. 2021b. "Background Press Call on Climate Security." Press Briefing, October 21. Washington, D.C.: The White House. Accessed June 30, 2023. https://www.whitehouse.gov/briefing-room/press-briefings/2021/10/21/background-press-call-on-climate-security/.

WHO Multicentre Growth Reference Study Group (WHO) and Mercedes de Onis. 2006. "WHO Child Growth Standards Based on Length/Height, Weight and Age." *Acta Paediatrica* 95 (S450): 76–85. DOI: https://doi.org/10.1111/j.1651-2227.2006.tb02378.x002E

World Bank. 2019. "Ending Learning Poverty: What Will It Take?" Washington, D.C.: World Bank. DOI: https://doi.org/10.1596/32553.

———. 2022. "Climate and Development in South Asia." Accessed June 30, 2023. https://www.worldbank.org/en/region/sar/brief/integrating-climate-and-development-in-south-asia/integrating-climate-and-development-in-south-asia-region.

World Population Review. 2023. "Muslim Population by Country 2023." Accessed June 30, 2023. https://worldpopulationreview.com/country-rankings/muslim-population-by-country.

Wun, Lap-Ming, Trena M. Ezzati-Rice, Nuria Diaz-Tena, and Janet Greenblatt. 2007. "On Modelling Response Propensity for Dwelling Unit (DU) Level Non-Response Adjustment in the Medical Expenditure Panel Survey (MEPS)." *Statistics in Medicine* 26(8): 1875–84. DOI: https://doi.org/10.1002/sim.2809.