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FLOODS, COMMUNITY INFRASTRUCTURE, AND CHILDREN'S HETEROGENEOUS LEARNING LOSSES IN RURAL INDIA

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ABSTRACT

India has the world's largest number of school-aged children. The majority live in rural areas, many of which are highly flood-prone. Previous studies document that in such areas, floods are associated with lower enrollments, attendance, and learning, in some cases with differentiation by gender, caste/religion, and family SES. Previous literature suggests that components of community infrastructure have positive associations with children's learning. However, previous literature has not addressed whether better community physical and social infrastructures are associated with (1) smaller flood-related learning losses on average, (2) different learning for marginalized versus other children in the absence of floods, and (3) different vulnerabilities to floods for marginalized versus other children. This paper finds that (1) most aspects of community physical and social infrastructure are not associated with lower flood-related learning losses on average, but proximity to towns and several components of social infrastructure are associated with lower flood-related learning losses on average, (2) community physical and social infrastructure components have heterogeneous associations, in some cases increasing, in most cases not affecting, and in other cases reducing disparities in learning between marginalized and other children in the absence of floods, and (3) community physical and social infrastructure components have heterogeneous effects, in some cases increasing, in most cases not affecting, and in other cases reducing disparities in learning between marginalized and other children in the presence of floods.

Highlights:

- Most infrastructural components not associated with flood learning losses
- Some infrastructure associated with lower average flood learning losses
- Infrastructure correlated heterogeneously with learning disparities absent floods
- Infrastructure heterogeneously associated with learning disparities when floods strike

Keywords: Education, learning disparities, climate disasters, floods, infrastructure effects, caste inequalities, Hindu-Muslim inequalities, social stratification

JEL: D63, I24, I25, I28, Q54, Q56

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1 Introduction

India's geophysical and climatic features make it one of the world's most disaster-prone countries — the country is ranked seventh in the 2021 global climate-risk index (Eckstein, Künzel, and Schäfer 2021; Patankar 2019). Moreover, India is becoming *more* susceptible to flooding over time, as a result of climate-change-induced increases in extreme precipitation events and ongoing population growth (Ali, Modi, and Mishra 2019), and floods accounted for over half of all natural and climate-related disasters in India since the 1990s (Patankar 2019). Children from marginalized groups often are at elevated risk of exposure, and generally have fewer resources to cope with flooding aftereffects. In India, caste, tribal status, and religion, along with gender and socioeconomic status, have historically constituted key dimensions of social stratification and related vulnerabilities.

A critical mechanism through which diminished living conditions due to climate change could occur, but one that is not yet well understood, is disruption of children's schooling and learning. Adverse climatic events, such as floods, can damage educational infrastructure. Emergency school closures and disruptions, which are common due to unpredictable, recurrent, and severe floods, can have significant adverse impacts on children's education. In India, floods may make transportation to schools difficult or impossible (Bertho et al. 2012), and evidence suggests that children from some marginalized populations are disproportionately exposed to floods (Khalid et al. 2024). Krishna, Ronan, and Alisic (2018) found that many children whose studies were disrupted by severe floods reported an inability to return to school after floods due to illness or loss of books and uniforms.

The physical and social infrastructure of a community can play crucial roles in bolstering the resilience of school systems and children, particularly in the face of natural disasters. Communities that are well equipped with adequate resources, strong physical and transportation infrastructures, histories of collective responses to crises, and norms of public safety and trust, may be better prepared to maintain school operations and support children's learning during these challenging times. Similarly, communities with local educational facilities that are widely viewed as functioning well, inclusive, with well-regarded and present teachers, and with strong school-family relationships may be more effective in resuming schooling and drawing children back in after disasters. However, these physical and social infrastructural effects may differ among different groups of children.

Although the previous literature has focused on the average effects of floods, their relative effects on marginalized children, and average effects of infrastructure, it has not addressed whether components of better physical and social infrastructure (1) are associated with reduced learning losses due to floods on average, (2) are associated with different learning for marginalized versus other children in the absence of floods, and (3) are associated with less or more vulnerability to floods for marginalized versus other children. A priori, in the presence of floods, such infrastructure could be protective on average and particularly protective for marginalized children or, in contrast, less for marginalized than for better-off children. Taking into account the possible differential infrastructure effects, the impacts of floods may increase or reduce diversity in learning outcomes. This paper utilizes Indian Human Development Survey data to address the questions, (1) are components of community physical and social infrastructure associated with reduced impacts of floods on children's learning, (2) do components of community physical and social infrastructure have heterogeneous associations across marginalized and non-marginalized children's learning in the absence of floods, and (3) do components of community physical and social infrastructure have heterogeneous associations with marginalized and non-marginalized children's learning losses in floods?

2 Background

The frequency and intensity of natural disasters, such as floods, are anticipated to escalate due to climate change, impacting a substantial portion of the global population (Hirabayashi et al. 2013). In assessing disaster impacts, a body of recent social science research adopts "an approach that sees disasters as social processes that can be very long term in both genesis and effects and are social in nature, not simply environmental or natural events" (Arcaya, Raker, and Waters 2020, 673, discussing Tierney 2019). This approach is crucial, especially since structures of social stratification result in uneven exposure and vulnerabilities to climatic and environmental risks (Frankenberg et al. 2013). For instance, entrenched social hierarchies based on gender, age, race, caste, religion, and/or socioeconomic status can play crucial roles in determining who is most vulnerable to disasters and who exhibits greater resilience (Enarson 2012; Khalid et al. 2024; Rauscher and Cao 2024).

2.1 *Natural disasters and children*

Due to their dependence on caregivers and greater vulnerability to specific environmental factors, children are more susceptible than others to adverse environmental conditions (Ebi and Paulson 2007; Frankenberg and Thomas 2017). Recurrent and extreme floods can impact children in multiple ways, including by inflicting immediate physical harm, causing structural damage to schools and healthcare facilities, and disrupting acess to educational and medical care. Studies from high-income countries (HICs) show that severe floods, which often lead to frequent emergency school closures and interruptions, significantly disrupt education, resulting in increased dropout rates and diminished academic performance (Azevedo et al. 2021; Marcotte and Hemelt 2008).

In low- and middle- income countries (LMICs), which often face resource constraints and have a lower overall capacity to address such shocks, children are among the most severely affected victims (Martin 2010; Norris et al. 2005; Shah et al. 2018). For instance, Pham (2022) found that monthly rainfall shocks in Vietnam were associated with lower enrollment among 7- to 18-year-old children, particularly those from ethnic-minority backgrounds. Similarly, Thamtanajit (2020) found that Thai children exposed to recurrent floods, resulting in extended school closures and damage to basic school facilities, performed more poorly on tests compared to non-exposed children.

Because destruction caused by disasters is a function not only of the events themselves but also of where and how societies build and the resources available to recover and respond, the adverse implications of disasters for children tend to be exacerbated in LMICs (Kousky 2016). Income and asset losses, coupled with disaster-related expenses, often force families in LMICs to pull children from school for labor. In Madagascar, floods reduced the probability of teenage school attendance and pushed students into labor markets, with girls especially likely to drop out and enter the labor force (Marchetta, Sahn, and Tiberti 2019). In general, financially strained households may struggle to afford healthcare, food, or educational supplies, significantly impacting children's physical and cognitive development (Dimitrova and Muttarak 2020; WHO Multicentre Growth Reference Study Group and Onis, n.d.). Natural disasters such as floods also increase the likelihood of households slipping into poverty, especially among those most reliant on natural resources for livelihoods. The absence of insurance coverage or government compensation programs can lead to long-term negative effects of such events on children's human capital, when low-income households struggle to maintain access to food, healthcare, and education (Baez, Fuente, and Santos 2010). Furthermore, the trauma from such events can lead to deteriorating mental health, which, in turn, can affect physical and cognitive well-being and academic performance (Frankenberg and Thomas 2017; Krishna, Ronan, and Alisic 2018). In general, natural disasters have the potential to worsen the educational crisis in LMICs, where nearly half of all children are already facing challenges in acquiring essential skills (Venegas Marin, Schwarz, and Sabarwal 2024).

2.2 *Community infrastructure and natural disasters*

Although climatic-change-induced risks have escalated to alarming levels in recent decades, individuals and societies have grappled with climatic hazards throughout their histories. In response to these challenges, some societies have developed strategies and infrastructures for protection and recovery, as well as adaptation to reduce future hazard risks (Adger 2003). At the level of communities, infrastructure can be defined and categorized in various ways, but one key distinction is between physical and social infrastructure (for a discussion, see Latham and Layton (2022)). In this conceptualization, physical infrastructure might be defined as "physical systems of water distribution, power provision, telecommunications and transport," and, in our case, education and health systems (660). The definition of social infrastructure that we adopt here draws on the notion of "people as infrastructure" (Simone (2004), cited in Latham and Layton (2022, 660))—the idea that "in the absence of formal physical infrastructures," or, by extension, alongside them, "the relationships between people, and the ways that [support and sustain] them, can be understood as forming a kind of infrastructure." Latham and Layton (2022) additionally make the important point that social, cultural, and political factors can warp access to infrastructure.

Evidence from various disciplines underscores the pivotal role that physical infrastructure plays in the post-disaster recovery of communities. Studies suggest that allocating resources towards physical infrastructure, along with proper disaster preparedness and post-disaster recovery management, would be a valuable investment for enhancing resilience and addressing community challenges (Opabola et al. 2023). In a comprehensive study, Khan, Anwar, and Batool (2022) investigate the relationships between various risk and resilience indicators and their associations with losses from natural disasters. This study spans a broad spectrum of countries over the period from 1995 to 2019, with resilience indicators including aspects such as infrastructure, institutional quality, and economic performance, among others. The study's findings demonstrate that improvements in these resilience indicators are associated with lower damage from natural disasters. For instance, countries with better infrastructure, including upper-middle, lower-middle, and low-income countries, experience less damage. High-income countries with improved information and communication technology and institutional quality see less damage. Enhanced food security and women's empowerment are associated with less damage in upper-middle-income and lower-middle-income countries, respectively. High- and low-income countries appear to benefit from improved economic performance and human capital, while a stronger emergency workforce is associated with less damage in upper-middle and lower-middle-income countries.

The role of social aspects of communities, often referred to as community social capital, in mitigating the adverse effects of natural disasters and fostering resilience remains relatively understudied in LMICs (Aldrich and Meyer 2015), perhaps due to challenges in determining key attributes that matter (Rockenbauch and Sakdapolrak 2017). Krishna (2002) and Serra (2001) argue that the conceptions of social capital applicable in HICs might be less appropriate in the cultural and normative landscape of LMICs.[2] Yet, with LMICs becoming increasingly susceptible to climatic-induced-risks, an emerging body of literature has begun to explore the buffering impacts of various forms of social capital. For instance, Akbar and Aldrich (2018) found a significant correlation between the community social capital of victims, measured as post-disaster social support and post-flood social and political trust, affected by the 2010 Pakistan floods and their recovery processes.[3] Similarly, community social capital, measured as the presence of civic and social organizations, attendance and participation in flood meetings, and membership in flood management associations, has been linked to community resilience in Ghana (Abunyewah et al. 2023). Community collective action groups, such as women's collectives in flood-affected areas in Nepal and community-based disaster risk management collectives in tsunami-impacted regions in Thailand, have been found to be associated with the development and reinforcement of communities' adaptive capacities (Ireland and Thomalla 2011). Similarly, following the 2004 Indian Ocean tsunami, coastal village communities in Tamil Nadu with strong caste, religious, and kinship ties helped in speeding up the recovery process (Aldrich 2014). While recognizing that "social capital" is a widely-used term in the development literature, we prefer in this analysis to use the related concept of "social infrastructure" as we have defined it, because it parallels the concept of physical infrastructure. Moreover, we treat the term as a non-normative community characterization: social infrastructure in various forms could be beneficial or harmful, and it could carry different implications for members of advantaged and disadvantaged groups in a community.

2.3 *Indian context*

The effectiveness of community infrastructures in enhancing people's capabilities often depends on societal structures of stratification, including caste, religion, class, gender, and place of residence. Aldrich (2012) points out that in certain situations, unequal access to social capital (or, by extension, social infrastructure) within communities can result in

2. There appears to be some consensus on two important forms of social capital. First, structural social capital encompasses social structures, organizations, and institutions that can prove crucial in mitigating the impacts of natural disasters and promoting social reorganization (Adger et al. 2005). Second, cognitive social capital revolves around mental processes, psychology, and the realm of ideas, particularly encompassing norms, values, attitudes, and beliefs (Cattell 2001; Forrest and Kearns 2001; Lin 2017; Woolcock 2002).

3. Post-disaster social support includes emotional, informational, and tangible support received from social networks, while post-flood social and political trust measures trust in neighbors and institutions like government and NGOs.

recovery efforts that primarily benefit privileged groups. This phenomenon can inadvertently intensify prejudices and further marginalize individuals on the peripheries. India, with its entrenched caste- and religion-based stratification, economic inequalities, and conservative gender norms, offers a rich context for exploring the effectiveness and limits of community infrastructures in promoting equitable resilience and adaptive strategies.

The caste system divides Hindus hierarchically into privileged upper castes and marginalized lower castes (Jodhka 2018), and scholars have documented multiple forms of discrimination and marginalization experienced by Muslims, India's largest religious minority group (Jaffrelot and Gayer 2012). Residential segregation of marginalized groups, associated with caste- and religious-based discrimination, has created conditions that systematically impede equitable access to education, employment, healthcare, and other essential services (Adukia et al. 2022; Betancourt and Gleason 2000; Hathi et al. 2018). Such forms of segregation are also consequential during natural disasters, where marginalized communities face systematic barriers in accessing relief assistance and recovery support (Aldrich 2010; Gill and DNN 2007; Krishna, Ronan, and Alisic 2018; Watch 2007).

Despite these challenges, rural communities also foster informal associations that are built on the pillars of mutual respect, trust, reciprocity, and a shared sense of goodwill. In a study across 69 villages in western and central India, Krishna (2002) found that the absence of conflicts and the presence of collective approaches to the addressing of societal problems are key elements of village social capital. This social capital drives both social and economic development and can be mobilized during crises, including natural disasters. Krishna (2002) also reports that respondents from villages with high levels of social capital were more likely to express confidence that their communities would unite to support each other during natural calamities. Other types of social collective, both formal, such as self-help groups, and informal, have the potential to enhance the agency and empowerment of members and mobilize networks for immediate action, relief work, and rehabilitation. For example, voluntary organizations such as self-help groups, which are known to improve access to public goods, expand women's capabilities (Anand et al. 2020; Subramaniam 2012), increase governmental program uptake (Saha, Annear, and Pathak 2013), aid in asset creation (Swain and Varghese 2009), and contribute to village development (Krishna 2002), could be similarly effective in disaster scenarios.

Finally, it bears noting that traditional forms of social capital may sometimes be challenged by individuals and groups asserting their rights over resources. India has a long history of social movements in which marginalized groups have resisted privileged and dominant groups (Mosse 2018). Social disharmony, particularly when it originates from movements that advocate for social justice, equality, and rights, can lead to beneficial outcomes for marginalized communities. These conflicts can drive substantial societal changes and policy reforms, strengthening resources and capacities of vulnerable groups, which can also prove beneficial during natural disasters. Although our study does not delve into the specific processes and mechanisms by which community infrastructure may benefit various groups, the aforementioned discussion emphasizes the necessity of a detailed contextual understanding to interpret the observed direction and magnitude of associations in our findings.

Khalid et al. (2024) used the Indian Human Development Survey (IHDS) to investigate the implications of flood exposure for the education of school-age rural children, with particular attention to children of marginalized groups. The results of that study indicated that lower-caste Hindu, Muslim, and poorer children with less-schooled parents in agricultural households were more likely to experience flooding. The results also showed that flood exposure was associated with disproportionately negative learning outcomes for girls and that households with better economic resources had a greater likelihood of mitigating flood-exposure effects on delayed school progress. The current study investigates whether flood-induced learning losses are mitigated by physical and social infrastructure and whether observed effect modifications differ for children from more-marginalized versus more-privileged backgrounds, defined in terms of caste/religion, gender, and socioeconomic status.

3 Research methods

3.1 Data

The India Human Development Survey (IHDS) is a longitudinal survey of over 41,000 households interviewed in 2004-5 and 2011-12, covering 971 urban blocks and 1,503 villages (Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019). Our analytic sample consists of 7,250 children from panel households who completed learning assessment tests in the second wave.[4]

3.2 Measures

Table 1 shows the measures used in the analysis, which we describe below.

Learning outcomes. To have a comprehensive picture of rural Indian children's learning skills, we generate an outcome measure that combines performance in reading, math, and writing skills. The IHDS used the same assessment criteria for all children aged 8-11 years, with tests designed to capture basic learning competencies. For math skills, children's performances were ranked from 1 to 4 in increasing order — cannot recognize numbers (1), able to recognize numbers (2), able to do subtraction (3), and able to do division (4). A similar ranking from 1 to 5 was used for reading skills — cannot recognize letters in the alphabet (1), can recognize letters (2), can read words (3), can read paragraphs (4), or can read stories (5). Writing skills were evaluated based on the number of mistakes made in writing simple sentences, with children making two or fewer mistakes receiving a rank of 1 and those making more than two mistakes a rank of 2. In Table 1, we present the mean levels of math, reading, and writing skills of the children in our sample.[5] Learning assessments were administered at home, so our analysis is not subject to selectivity bias due to school enrollment or attendance, unlike analyses based on tests administered in schools. Access to test-score data means that our investigation considers learning and not just school attendance or school enrollment, which is often the case in much of the literature.

Finally, to create comparable measures across the three different assessment scales, we generated composite measures of children's learning skills by first standardizing children's performance scores in each of the three tests[6] and then calculating the average of these standardized scores. Cronbach's alpha for the composite score is 0.82, suggesting good internal consistency (Tavakol and Dennick 2011).[7]

Flood exposure. The flood-exposure measure that we use is *village flood exposure*, which is a dichotomous measure with a value of 1 if the village was exposed to floods at least once between 2006 and 2011 and 0 if it was not exposed to floods during this period. This measure is based on the information collected in the village module on village-level recent flooding histories for each year between 2006 and 2011.[8] We also define a state-level flood exposure measure as the percentages of PSUs or villages in the state exposed to one or more episodes of floods between 2006 and 2011. This measure allows us to control for states that are predisposed to floods and those that experience more frequent and severe floods.

4. In both survey rounds, learning assessments were administered only to children who were 8-11 years of age at the time of the survey. Consequently, the children in our analytic sample, who were 8-11 years old in the second wave, were too young to have been eligible for assessment in the first wave.

5. All three tests were based on standardized test modules developed with the help of PRATHAM, an educational NGO, and are widely employed in assessing learning among children in many contexts (Desai et al. 2010). The tests were translated into regional languages to facilitate easy administration and reduce anxiety levels among children.

6. By standardizing the performance in the achievement tests to have means 0 and standard deviations of 1, we ensure that these have a common scale.

7. Apart from the overall alpha value, we also compute item contributions of each score. Our results show that each item has high item-test and item-rest correlations, indicating that they are all good measures of the overall learning-skill construct.

8. An ideal measure of flood exposure would capture the intensity of exposure through information on both the frequency of floods within a year and their duration. However, IHDS does not collect this detailed information. An alternative measure that we could have used is the count of years with reported floods. However, this measure would still not capture flood intensity, as it cannot tell us whether floods in a given year were brief or prolonged, or whether there were multiple flood episodes. We therefore use a more parsimonious binary classification of flood exposure.

Community infrastructure. Our community infrastructure measures are derived from the village and household modules. We focus on a specific set of measures designed to capture the *physical* and *social* infrastructures of communities that possibly play crucial roles in mitigating the impact of flood exposures on children's education. Detailed definitions of these measures are provided in Table 1A of the appendix. We used seven *physical* and eleven of the twelve *social* community measures from the initial IHDS wave, ensuring that they are not influenced by flood experiences between waves. An additional measure, with respect to village residential segregation, was only collected in the second wave. The information in the household module comes from reports of knowledgeable household member(s), but the village module gathered insights from community members, usually village officials, providing their informed perspectives on different aspects of their communities.

The *physical* infrastructure measures include five measures from the village module. *Distance to town*, measured in kilometers, captures the proximity of the surveyed village to the nearest town. *Households electrified* is the reported fraction of households in the village with electricity. *Road usable during monsoon* is a dummy variable indicating whether the main road in the village was usable during the monsoon (1=yes, else 0). The *middle/secondary school* and *medical facilities* are dummy variables indicating the presence of public or private middle or secondary schools, and public or private healthcare centers within the village (1=yes, else 0).

The final two measures of physical infrastructure, *primary drinking water source (piped)* and *toilet ownership*, are derived from household reports. These represent the community-wide proportions of households with piped drinking water and toilet facilities. We categorize the household reported primary source of drinking water as either piped (1) or other sources (0), which include hand pumps, wells, ponds, etc. Similarly, households are coded as toilet owners (1) if they own a toilet, including a septic pit, and as non-owners (0) otherwise. The village averages of these binary variables yield the measures for *primary drinking water source (piped)* and *toilet ownership*.

The *social* infrastructure measures include *communal living arrangement*, *social organizations (number)*, *safe against crimes*, *free of conflicts*, *communal problem solving*, *educational quality*, *teachers are present in school*, *teachers seen as fair and unbiased*, *teachers don't employ corporal punishment*, *teachers are local residents*, *parent/household-teacher engagement*, and *large village*. All of these measures are aggregated to the community level from the household module except for *communal living arrangement*, *social organizations*, and *large village*, which are from the village module.

The *communal living arrangement* is a binary measure. It is assigned a value of 0 if households from different social groups live in segregated settlements, and a value of 1 if these households coexist within the same settlements. *Social organizations* is the count of village formal associations, including self-help groups, caste, religious, youth, and cooperative collectives.

The *safe against crimes* measure represents community-level safety. Households were asked about instances of theft, unlawful break-ins, violent attacks, and harassment of unmarried girls in the past year. To generate a community-level safety measure, we summed the occurrences of these four crime types per household, and standardized the outcomes to generate values between 0 and 1 (1 signifying the absence of any crimes and 0 indicating all four crimes occurred). In the last step, we obtained the *safe against crimes* measure by computing the mean across all households in the village. The *free of conflicts* measure is an indicator of two types of conflicts within the village: conflicts between individuals and conflicts among different groups. Each surveyed household provided separate reports on the occurrence of these conflicts. Following a similar approach to the crime assessment, we initially derived a household-level measure indicating the absence of conflicts. Subsequently, this information was used to compute the village-level *free of conflicts* measure. *Communal problem solving* measures the fraction of households at the village level reporting the resolution of community issues through collective efforts.

Educational quality is a composite measure derived from children's reading, math, and writing skills based on tests administered to 8 to 11-year-olds in the 2004-2005 round of the IHDS survey. Similar to the *learning skills* measure, it was generated by first standardizing children's performance scores in each test and then averaging these standardized scores. Finally, the *educational quality* score at the village level was calculated by averaging the learning skills scores of all children within a given village.[9] *Teachers generally present in school* measures the fraction of households reporting regular attendance of village school teachers. *Teachers are seen as fair and unbiased* reflects households' perceptions of school teachers treating children impartially and without bias toward specific social groups. It is measured as the proportion of households that perceive teachers as fair and unbiased. *Teachers are local residents* is the fraction of households reporting that teachers who work in village schools reside within the same village. *Parent/household-teacher engagement* is the proportion of households within the village that frequently engage with their children's teachers to discuss their educational progress. Lastly, *large village* captures the size of the village based on population estimates classified by IHDS into three segmentsless than 1000, between 1000-5000, and over 5000. We combine the first two categories into 'small villages' (0) and code the last category as 'large villages' (1).

These multifaceted community measures provide valuable insights into the broader community environments and their potential impacts on children's learning outcomes, including, in particular, the interactions between flood exposure and community characteristics.

Household background variables. These data include detailed information on background characteristics linked to socio-demographic status and marginalized identities — children's gender and age, caste, religious affiliation, income and parental schooling attainments. These variables permit the investigation of differences in flood-burden modifications due to infrastructure on children's learning outcomes by potentially important stratifiers.

In our subgroup analysis, we group historically marginalized Hindu castes Other Backward Castes and Scheduled Castes and Scheduled Tribes or Indigenous groups into a category termed Hindu Marginalized Castes (Hindu MC), contrasting them with the historically privileged Hindu Upper Castes (Hindu UC). It's important to note that Scheduled Tribes or Indigenous people might not exclusively identify as Hindu, and our classification primarily reflects their historical marginalization. Thus, for the subgroup analysis, we categorize participants into three groups: Hindu UC, Hindu MC, and Muslim. Similarly, we classify our sample into 'rich' and 'poor' groups by combining the top three and bottom two household income quintiles, respectively.

3.3 Model specifications

We estimate the following specification:

$$E_{i,h,c} = F_c\beta + C_c\left(\delta + F_c\gamma + M_{i,h,c}\theta + F_cM_{i,h,c}\psi\right) + X_{i,h,c}\lambda + \varepsilon_{i,h,c} \quad (1)$$

where $E_{i,h,c}$ is learning skill of child i in household h in community c in 2011-12; F_c is the community flood experience between 2004-05 and 2011-12; C_c is a vector with community physical and social infrastructure characteristics in 2004-05 (except for *community living arrangement* which comes from 2011-12); $M_{i,h,c}$ is the marginality status of child i in household h in community c in 2004-05; $X_{i,h,c}$ is a vector of controls in 2004-05; $\varepsilon_{i,h,c}$ is a vector of disturbance terms; and $\beta, \delta, \gamma, \theta, \psi$, and λ, are vectors of parameters to be estimated. β is the vector of estimated impacts of floods on educational outcomes that are negative if floods reduce learning skill; δ is the estimated association between community-level physical and social infrastructure on learning; γ is is a vector of estimated heterogeneities of these impacts for the same educational outcomes due to flood exposures; θ is a vector of estimated differential learning outcomes by children's marginality status (social group, sex, household income, and parental education); ψ is estimated learning loss gaps due to interactions between floods and children's marginality status. We first estimate the main effects for floods and infrastructure and then consider estimates for the three questions of interest:[10]

9. The Cronbach's alpha for the test scale is 0.8489, which indicates a high level of internal consistency among the items.

10. Our model specification is designed to directly test our research questions about infrastructure's moderating role in flood impacts. While individual fixed effects models or lagged individual learning outcomes cannot be used because children in our analytic sample were tested only in Wave 2, we incorporate historical educational context through our village-level educational quality measure from Wave 1. The effects of interactions between flood exposure and household characteristics are examined in detail in Khalid et al. (2024).

(1) ***Do children in villages with better infrastructure have smaller learning losses when exposed to floods?*** We estimate specification (1) without taking into account the marginality status of children (i.e. with θ and ψ set to zero) to answer our first research question. If an element of physical and social infrastructure is associated with smaller (larger) learning losses due to floods, the corresponding element in γ is positive (negative).

(2) ***Are components of infrastructure associated with different learning outcomes for children from more-marginalized versus other groups in the absence of floods?*** We estimate specification (1) without accounting for the village-flood-exposure interactions (i.e. with γ and ψ set to zero) separately for each marginality group. Here again, if an element of the physical and social infrastructure is associated with smaller (larger) learning losses of children from more-marginalized groups relative to other groups, the corresponding element in θ is positive (negative).

(3) ***Are components of infrastructure associated with smaller learning-loss gaps due to floods between children from more- versus less-marginalized groups?*** We estimate specification (1) accounting for the village-flood-exposure interactions (i.e. with γ and ψ not set to zero) separately for each marginality group. If an element of physical and social infrastructure is associated with higher (lower) learning outcomes of children from more-marginalized groups relative to other groups, the corresponding element in ψ is positive (negative).

Second-wave test-taking-propensity weights. 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 due to outmigration or other factors, we weigh our second-wave observations using the inverse of each child's propensity to take the tests in the second wave as predicted by first-wave characteristics.

Multiple-inference corrections. Our model specification involves testing multiple hypotheses simultaneously. Traditional p-values from regression estimation treat each hypothesis as an independent test. However, in a setting with multiple simultaneous hypotheses, relying on p-values can lead to an increased risk of falsely rejecting true null hypotheses. To ensure the robustness of our inferences, we apply multiple-inference corrections. Specifically, we calculate the q-values using the Benjamini, Krieger, and Yekutieli (BKY) approach, as detailed in Anderson (2008). The BKY method is a two-stage procedure that controls the False Discovery Rate (FDR) by estimating q-values, which adjust for the potential over-rejection of null hypotheses when many tests are conducted simultaneously. If a coefficient is significant at q-values ≤ 0.1, it indicates that the expected proportion of false positives (incorrectly rejecting the null hypothesis) among the significant results is at most 10 percent.

4 Results

4.1 Descriptive statistics

Table 1 presents descriptive statistics for math, reading, writing skills, composite learning skills, community flood exposures, and infrastructure measures. In India, children aged eight to eleven usually attend grades two through six. The average math score of 2.34 suggests that most children performed well in number recognition but faced challenges with basic arithmetic, particularly subtraction. Likewise, the average reading score of 3.33 implies that while the majority of children could read individual words, they struggled to comprehend entire paragraphs or more complex skills such as reading a story. The mean writing skill score of 1.68 indicates that children on average made more than two mistakes when writing even simple sentences. The mean of the composite learning skills measure is -0.06, suggesting that, on average, the learning skills of the children who took the tests in 2011-12 are close to the mean of the standardized distribution, as would be expected.

Approximately a third of the children resided in villages affected by floods between 2004-05 and 2011-12. On average, about 32 percent of villages within each state experienced flooding during this period. In terms of physical infrastructure, our sample children lived in villages that were situated, on average, about 14 kilometers from the nearest town. Around 56 percent of households, on average, had electricity; approximately 75 percent, 66 percent, and 54 percent of villages had roads that were usable during the monsoon season, had middle or high schools, and had medical facilities, respectively. Furthermore, only one in five households, on average, had access to piped drinking water and flush toilets.

In terms of social infrastructure, about one in three villages was stratified with people from different social groups living in segregated settlements. On average, these villages had around four active social organizations. Concerning safety and conflict resolution, about nine out of ten villages reported relative safety from crimes like theft, robbery, break-ins, and violence. Additionally, seven out of ten villages were relatively free from conflicts, and six out of ten villages commonly resolved societal issues through collective efforts.

In terms of educational quality, the mean value of -0.33 suggests that learning skills in an average village in 2004-05 are generally lower than the overall average, albeit with considerable variation among the villages in our sample. Regarding household perceptions of teachers and schools, a significant majority believed that teachers were usually present in schools and treated children from diverse social groups fairly and impartially. Additionally, over three-quarters of households reported that their children had not been physically punished in school. Nearly half of the households mentioned that schools in their village primarily employed locally resident teachers. On average, in four out of ten villages, parents and other household members regularly met with class teachers to discuss their children's progress in school.

With regard to the background of the students, Table 2 presents sample distributions of flood exposure by background characteristics. No significant differences observed by gender or age. However, children of Hindu Other Backward Castes, Muslim, and Hindu Scheduled Caste – groups that are marginalized – show the highest likelihood of flood exposure. In contrast, Scheduled Tribes and Indigenous children, who are also highly marginalized, tend to reside in forested or hilly areas and experience relatively lower exposure to floods. Additionally, children from households in higher income quintiles and those with higher parental schooling attainment tend to experience lower flood exposures.

4.2 Multivariate estimates

We first start with the main effects on learning for floods and infrastructure as part of evaluating our research questions. Table 3 presents estimates of relation (1) with the "main effects" on children's learning skills of floods, β, and of physical and social infrastructures, δ, and interactions between floods and physical and social infrastructures, γ. The main effects coefficient estimates for village flood exposures and state flood exposures control are both negative and statistically significant, suggesting that children in flood-exposed villages on average are behind in learning skills. Specifically, children in villages exposed to floods have learning skills that are, on average, 0.084 standard deviations lower than those in non-flooded villages. Furthermore, for each percentage point increase in state flood exposures, learning skills are lower by 0.004 standard deviations.

In terms of physical infrastructure, proximity to the nearest town, electrification, and toilet ownership are significantly associated with higher learning. For each additional kilometer from the nearest town, the learning skills are lower by 0.004 standard deviations. Since an average child in our sample resides 14 km from the nearest town, this equates to a reduction of roughly 0.056 standard deviations in learning skills for the typical person. Children in households with electricity have learning skills that are, on average, 0.115 standard deviations higher than those in households without electricity. Children in communities with high toilet ownership have learning that is, on average, 0.246 standard deviations higher than children in communities with low toilet ownership. Surprisingly, however, the presence of middle/secondary schools is associated with lower learning by 0.107 standard deviations.

These findings remain robust even after correcting for multiple hypothesis testing. Specifically, we find very strong evidence for the impact of distance to town and household electrification ($q-value \leq 0.05$). In addition, the significance of toilet ownership is also supported ($q-value \leq 0.10$). The use of FDR q-values is crucial due to the increased risk of Type I errors (false positives) inherent in multiple hypothesis testing. By controlling the false discovery rate, we ensure that the significance of our findings is not merely due to chance. This approach strengthens the reliability of our hypothesis tests based on p-values, as it accounts for the potential inflation of false positives when multiple comparisons are made.

Regarding social infrastructure, communal living arrangements, communal problem solving, educational quality, and teacher presence in school are significantly associated with greater learning. Communal living arrangements indicating whether households across social groups live in mixed neighbourhoods, are associated with higher learning by 0.067 standard deviations. In villages characterized by active communal problem-solving, where residents collectively address village-related issues, we observe a 0.141 standard deviation increase in children's learning. Furthermore, a higher baseline of average learning skills at the village level, as indicated by the educational quality measure, is associated with an individual learning gain of 0.102 standard deviations. This implies that children residing in villages with a historical precedent of superior learning environments tend to exhibit better individual performance in second-round tests. The presence of teachers in schools is associated with higher learning by 0.166 standard deviations, suggesting that higher levels of teacher attendance are crucial for improved learning among children. Interestingly, we observe that in villages where school teachers reside in the same village as their school, student learning outcomes are lower by 0.07 standard deviations. These findings remain significant based on q-values, further validating the robustness of our results.

Similar negative associations between floods and learning and generally positive associations between infrastructure (particularly physical infrastructure) have been presented in the previous literature. Our contribution is to go beyond such main effects on learning of floods and of infrastructure to investigate three major questions pertaining to differences from the main-effects learning losses due to infrastructure and marginality status. All the estimates summarized below for our three main questions are in addition to the main effects.

(1) ***Do children in villages with better infrastructure have smaller learning losses when exposed to floods?*** As noted in the introduction, previous literature has not addressed whether better physical and social infrastructures on average mitigate children's learning losses.

The last column of Table 3 shows estimates on the interactions between village flood exposures and components of community physical and social infrastructure. 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 particular components of the physical and social infrastructure.

In terms of physical infrastructure, only the distance from the nearest town is statistically significant. The negative interaction suggests that the adverse effect of being farther from town on learning skills is associated with less learning in flood-affected villages. For each additional kilometer from the nearest town, the learning-skills score is smaller by an additional 0.005 standard deviations in villages exposed to floods. This finding remains robust even after controlling for multiple hypothesis testing, with q-values providing strong support for this relationship.

The positive interaction estimates for flood exposures with certain aspects of social infrastructure indicate that these aspects of social infrastructure are associated with higher children's learning skills in the presence of floods than in communities without these infrastructure components in the presence of floods. Specifically, flood exposure in interaction with safety from crimes such as theft, break-ins, violent attacks, and harassment of girls has a highly significant coefficient estimate, with children in areas perceived as safe from crimes having learning losses that are, on average, 1.032 standard deviations lower in flood-affected villages than children in areas perceived as not safe but also in flood-affected villages. Similarly, a higher baseline educational quality at the village level is associated with lower learning losses by 0.060 standard deviations in the face of floods than in villages with lower educational quality in the face of floods. The perception of teachers as fair and unbiased is another key factor, with significantly lower learning losses by 0.667 standard deviations in flood-affected areas relative to flood-afflicted areas in which teachers are not perceived as fair and unbiased. Additionally, regular parental engagement with teachers is associated with learning losses that are 0.132 standard deviations smaller when there are floods relative to flood-affected villages without regular parental-teacher engagement. The marginally significant associations of a greater number of active social organizations and being in larger villages suggest possible protective effects of these measures in the presence of floods relative to flood-affected villages that have fewer active social organizations or are smaller. Furthermore, all except the perception of teachers as fair and unbiased, parental engagement with teachers, and social organizations are significant based on q-values, which provide stronger evidence for the robustness and reliability of these relationships.

The negative interaction estimates highlight infrastructure factors that are associated with lower learning skills in the presence of floods than are found without these infrastructure factors in the presence of floods. A negative interaction for *teachers are present in school*, a measure reflecting household perception of teacher attendance in the village school, is statistically significant and remains so at $q \leq 0.10$, implying that higher teacher attendance is associated with learning losses that are 0.348 standard deviations higher during floods relative to non-flood situations. The marginally significant negative interaction for *free of conflicts* indicates that in flood-affected villages, lower conflicts among people are associated with greater learning losses. However, this measure is not significant after adjusting for multiple hypothesis testing, suggesting that the observed effect might be due to chance.

(2) ***Are infrastructure components associated with different learning outcomes for children from marginalized versus other groups in the absence of floods?*** As noted, the interaction terms between community infrastructure and children's marginality status, θ, capture these possible heterogeneous effects. Figures 1, 2, 3, and 4 present the estimates of θ through the marginality status by community infrastructure interaction plots on the left of each figure.[11] The four figures refer, respectively, to four dimensions of marginalization: caste-religious groups, gender, socioeconomic-income and socioeconomic-parental schooling. In all figures, panel (a) presents the interaction coefficient estimates for physical infrastructure and marginalized groups, and panel (b) presents the interaction coefficient estimates for social infrastructure and marginalized groups, each with their 95 percent confidence intervals. Statistically significant coefficient estimates are shown in colored shades, whereas non-significant ones are shown in lighter shades. The plot indicates significance based on both conventional p-values and FDR q-values. Coefficient estimates are displayed as follows: red if significant at both p-values $\leq$ 0.05 and q-values $\leq$ 0.05; green if significant at q-values $\leq$ 0.10; blue if significant at p-values $\leq$ 0.05 but not significant by q-values; and grey if not significant by p-values. Note that whenever an estimate is significant by q-values, it is also significant by p-valuein the figure, this can be ascertained by looking at their confidence intervals. "Statistically significant" means significantly different for the more-marginalized group from the relevant other group. We discuss here the marginal associations as reflected in the coefficient estimates for the "double" interactions, not the total associations that would also include those discussed at the start of this section. The complete tables of estimates can be found in the Appendix.

Caste-Religious Groups: Figure 1 presents the interaction coefficient estimates (C-R) between community infrastructure and children from two marginalized groups, Hindu MC and Muslim, using the privileged Hindu UC as the reference category for both. The interaction coefficients between infrastructure variables and children's social groups provide insight into how the associations of community infrastructure with learning skills differ among these groups compared to the reference categories. Some infrastructure components are associated with higher learning for Hindu MC and Muslim children relative to Hindu UC children, while others are associated with lower learning for the marginalized groups.

The interaction coefficient estimates corresponding to caste-religious groups and physical infrastructure are shown in panel (a) of the figure. For Hindu MC children, living in villages with roads usable during the monsoon season is significantly associated with learning losses compared to Hindu UC children. However, the blue color indicates that this association is not significant based on the q-values, suggesting that it could be due to random chance. No other community physical infrastructure measure has statistically significant associations.

Panel (b) of the figure presents estimates corresponding to social infrastructure. The presence of a larger number of social organizations is associated with significantly lower learning losses for Hindu MC children compared to Hindu UC children, indicating that these organizations may provide more effective support or resources to Hindu MC children. Similarly, villages with greater engagement between parents and school teachers show significantly less learning losses for Hindu MC children compared to Hindu UC children. For Muslim children, living in more populous

11. See Table 2A and Table 3A in the Appendix for the complete estimates corresponding to Figure 1 and Figures 2, 3, and 4, respectively.

villages is associated with significantly smaller learning losses compared to Hindu UC children. However, none of these estimates remain significant after accounting for multiple comparisons, indicating that the evidence is likely weak.

Gender: In Figure 2, the "double" interaction coefficient estimates illustrate how the relationship between gender and learning losses varies with physical and social community infrastructure. Specifically, significant positive coefficients on infrastructure indicate that such infrastructure is associated with lower learning losses among girls relative to boys. Significant negative coefficient estimates, in contrast, suggest that such infrastructure is associated with greater girls' learning losses than for boys.

Panel (a) of the figure presents the coefficient estimates for interactions between girls and physical infrastructure. The positive and statistically significant coefficient estimate for electrification, based on both p-values and q-values, indicates that village electrification is associated with smaller learning losses for girls compared to boys. Additionally, the positive and statistically significant coefficient estimate for the distance to town suggests that each additional kilometer from the nearest town is associated with slightly less learning loss for girls compared to boys. However, this estimate is not significant based on the q-values, implying that the observed effect might be due to random chance and should be interpreted with caution.

Panel (b) displays the coefficient estimates for the interactions between girls and social infrastructure. The negative and statistically significant coefficient estimate for safe against crimes indicates that greater safety against crimes in the village is associated with larger learning losses for girls compared to boys. The significance at q-values ≤ 0.05 further suggests this evidence is strong. On the other hand, the positive and statistically significant coefficient estimate for *educational quality* suggests that a higher quality of education in villages is associated with smaller learning losses for girls compared to boys. Lastly, the negative and statistically significant coefficient estimate for the absence of corporal punishment by school teachers implies that the absence of such punishment is associated with greater learning losses for girls compared to boys. However, the last two estimates are not significant based on q-values, indicating that these effects might be due to random chance and should be interpreted with caution.

Socioeconomic status: Figures 3 and 4 present the interaction coefficient estimates between community infrastructure and two socioeconomic measures for childrenhousehold income and parental education.

First, consider household income, shown in Figure 3. The interaction estimates plot (Poor) demonstrate how the learning skills of poorer children vary relative to those of richer children based on the level of community infrastructure.

Panel (a) presents estimates for physical infrastructure. The significant negative association between electrification and learning skills suggests that electrification is associated with greater learning losses for children of poorer households compared to those from richer households. Similarly, the presence of middle and secondary schools is associated with greater learning losses of children from poorer households compared to those from richer households. This might reflect that children from the richer households benefit more from the presence of these schools.

Panel (b) displays the estimates for social infrastructure. Greater safety against crimes in villages and a community free of conflicts lead to smaller learning losses for children from poorer households compared to those from richer households. Furthermore, living in a village with a larger population is associated with smaller learning losses for children from poorer households compared to those from richer households. However, greater parental engagement with teachers is associated with larger learning losses for children from poorer households compared to those from richer households. However, none of these estimates are statistically significant based on the q-values.

Next, consider the parental schooling context shown in Figure 4. The figure plots the estimates of the interaction coefficients between the community infrastructure and children with no parental schooling (No School), using "some schooling" as the reference category. The interaction coefficient estimates demonstrate the differential associations of community infrastructure with learning skills between children whose parents have no schooling and those whose parents have some schooling.

Panel (a) of the figure provides estimates for physical infrastructure. The interaction coefficient estimate for parental education with no schooling and electrification is negative and statistically significant. Combined with the positive main effect of electrification (see Table 3A in the appendix), this pattern suggests complementarity - while village electrification benefits learning overall, children whose parents have some schooling benefit more from it than those whose parents have no schooling. This finding is also significant at q-value $\leq$0.05. Other measures of physical infrastructure have no significant interaction estimates.

Panel (b) of the figure presents estimates for social infrastructure. The interaction coefficient estimate for parents with no schooling and social organizations is positive and statistically significant, indicating that the presence of social organizations is associated with lower learning losses for children whose parents have no schooling, compared to those whose parents have some schooling. Similarly, the interaction coefficient estimate for parents with no schooling and a conflict-free community is positive and statistically significant. This implies that a harmonious community environment is associated with lower learning losses of children whose parents have no schooling, compared to those whose parents have some schooling. Additionally, the interaction coefficient estimate for parents with no schooling and "communal problem solving" is positive and statistically significant. Thus, in communities where people and groups collectively redress their conflicts and other forms of social problems, learning losses are lower for children whose parents have no schooling compared to those whose parents have some schooling. All these estimates are also significant at both p and q values $\leq$ 0.05, providing strong and robust evidence for our findings.

(3) ***Are components of infrastructure associated with smaller learning-loss gaps due to floods between children from more- and less-marginalized groups?*** As noted in the introduction, previous literature has not addressed whether better physical and social infrastructures are associated with less or more vulnerability to floods for marginalized versus other children. A priori, learning associations in the presence of floods with such infrastructure may be higher or lower for marginalized children than for other children. Recall that here we are addressing only the marginal impacts of infrastructure for historically marginalized versus privileged children. Of course, floods may reduce learning for all children on average, as indicated in the estimates at the start of this section but, depending on infrastructure, it may increase or reduce learning disparities. When we say "larger" or "smaller" in our descriptions below, we are only referring to disparities in learning losses associated with floods.

The coefficient estimates and the corresponding 95 percent confidence intervals plotted on the right sides of Figures 1, 2, 3, and 4 address whether associations between community infrastructures and floods are higher or lower for marginalized versus other children, thereby implying differential learning inequalities associated with floods. We discuss here the associations (i.e., second cross derivatives with respect to floods and marginality status) as reflected in the coefficient estimates for the "triple" interactions, not the total associations that would include also those discussed above.

Caste-Religious Groups: Figure 1 plots interaction coefficient estimates by children's caste and religion. The left and right panels show estimates for physical and social infrastructure component interactions, respectively. The Hindu MC and Muslim estimates are indicated by squares and diamonds, respectively.

In panel (a), which presents results for physical infrastructure interactions, we find that none of the physical infrastructure measures have any statistically significant triple interaction estimates. This suggests that physical infrastructure is not associated differently with learning losses of marginalized Hindu MC and Muslim children compared to privileged Hindu UC children in the context of flood exposure.

Panel (b) presents the results for social-infrastructure measure interactions with caste/religion. For children of Hindu MC, the positive and significant coefficient for *safe against crimes* suggests that residing in villages that have lower crime prevalence is associated with a significant *lowering* of learning disparities relative to their Hindu HC counterparts. Similarly, for Muslim children, the positive and significant coefficient estimate for the triple interaction for *free of conflicts* suggests that residing in villages with fewer interpersonal and inter-group conflicts is significantly associated with lower learning losses relative to Hindu HC children. These results suggest that for marginalized Hindu MC and Muslim children, living in a safe or harmonious village reduces the negative impacts of floods on learning losses more than it does for Hindu UC children, thereby reducing disparities between these groups. Both estimates remain statistically significant at q-value ≤ 0.10, indicating that these associations are fairly robust even after adjusting for multiple hypothesis testing. On the other hand, the negative and significant coefficient estimate for having a Parent-Teacher Association (PTA) suggests that for Hindu MC and Muslim children, the presence of a PTA is associated with larger learning losses when there are floods relative to Hindu HC children, indicating greater disparities between these groups. These estimates are also statistically significant at q-value ≤ 0.10. These findings suggest that while PTAs may generally on average be beneficial, they may also be associated with greater disparities in flood impacts on learning losses between marginalized and non-marginalized children.

Gender: Figure 2 plots the interaction coefficient estimates of village flood exposures and community infrastructure measures for girls. Panel (a), which corresponds to the physical infrastructure, shows that none of the triple coefficient estimates are statistically significant. Therefore there is no evidence of differences in learning associated with physical infrastructure in the presence of floods for girls versus boys.

Panel (b), which presents estimates for triple interactions with social infrastructure measures with floods and gender, reveals a mixed picture. The negative and significant coefficient for *educational quality*, a measure of children's learning skills in the first survey wave and therefore reflecting the historical learning context in the village, suggests that flood exposure in such villages results in *higher* learning losses among girls relative to boys. This finding implies a widening of the learning disparity between girls and boys during floods in villages with a historically superior learning context. On the other hand, the positive and significant coefficient estimates for having a teacher who does not punish students and the presence of a PTA indicates that these community features are associated with smaller learning loses during floods for girls relative to boys, indicating a reduction in disparities between girls and boys in this context. However, none of these estimates have significant q-values, suggesting that the evidence is not strong and does not hold after adjusting for multiple hypothesis testing.

SES: Figures 3 and 4 present the triple interaction estimates of community infrastructure and flood exposure with two separate socioeconomic indicators: household poverty and parental education (no schooling), respectively. First, consider household incomes, shown in Figure 3. For physical infrastructure, shown in panel (a), the positive coefficient estimate for village electrification indicates that electrification is associated with smaller learning losses in the presence of floods for children from poorer households compared to those from richer households. The negative coefficient for medical facilities is significant, which suggests that their presence in the village is associated with higher learning losses for children from poorer households than for those from richer households, implying increased disparities. However, neither of these estimates are statistically significant in terms of q-values. In contrast, the positive coefficient for a high prevalence of piped water as the primary source of drinking water in villages, significant in terms of both p-values and q-values, suggests that during floods, being in communities with high prevalence of piped water is associated with smaller learning losses for children from poorer households than for those from richer households, thus reducing disparities.

For social infrastructure, shown in panel (b), the negative coefficient estimate for having impartial teachers indicates that social infrastructure is associated with greater learning losses during floods for children from poorer households than for those from richer households.[12] This suggests greater disparities between poorer and richer children in the context of floods when teachers are impartial. This estimate is also statistically significant at q-value ≤ 0.10, indicating that the observed association remains fairly robust even after adjusting for multiple hypothesis testing.

12. The negative coefficient on *Teachers seen as fair and unbiased* that emerges in the three-way interaction between flood exposure, poverty status, and teacher impartiality, is surprising. This variable has a weak correlation (0.25) with *Teachers are present in school* (and is only very weakly correlated with other variables). The coefficient becomes insignificant when we estimate a model without the *Teachers are present in school* measure. Moreover, the coefficient estimate also becomes positive when interacted with *Village flood exposure* alone. We don't want to over-interpret these findings due to their sensitivity to specification. However, one possible interpretation is that teachers who focus on helping marginalized students when they are particularly vulnerable could be viewed by parents of other students as unfair. Alternatively, teachers who are perceived as "fair/unbiased" might be following strict rules of equal treatment even during disasters, when some students (particularly poorer ones) might need more additional support or flexibility. During floods, when poor students need extra support to overcome additional barriers (like disrupted schooling or displacement), this formal approach to fairness might be particularly detrimental.

Next, consider the parental schooling context. As shown in panel (a) in Figure 4, the positive coefficient estimates for having more electricity in villages and having more piped water in villages indicate that for children with no parental schooling, having more electricity in villages and having more piped water in villages are associated with lower learning losses during floods than for children with some parental schooling. This suggests a reduction in the disparities between these two groups. However, these associations lose their statistical significance once adjusted for multiple hypothesis testing.

In panel (b), which corresponds to social infrastructure, the positive coefficient estimate for teacher presence indicates that for children whose parents have no schooling, having teachers present is associated with smaller learning losses during floods compared to children whose parents do have some schooling. This suggests a reduction in the disparities between these groups in the context of floods in communities where teachers are generally present. However, this association is not significant in terms of q-values. In contrast, the negative coefficient estimate for the presence of a Parent-Teacher Association (PTA) for children with no parental schooling during floods is significant in terms of q-values. This suggests that the presence of a PTA is associated with greater learning losses for children whose parents have no schooling compared to those whose parents have some schooling, thus increasing the disparities between these two groups in the context of floods.

5 Summary and conclusions

In rural India, flood exposures are associated with poorer educational outcomes for children, and children of certain marginalized caste/religious, gender, and socioeconomic backgrounds are more likely than others to experience floods (Khalid et al. 2024). In this paper, we first show negative associations between children's learning and floods on average and positive associations with children's learning and selected infrastructure components. We then go beyond the previous literature by considering whether facets of physical and social infrastructures are associated with reduced learning losses for children in flood-exposed communities, and whether children from marginalized backgrounds have more, equal, or less learning associated with infrastructure in the absence of and in the presence of floods. Given that our model specification involves testing multiple hypotheses simultaneously, we have applied multiple-inference corrections to ensure the robustness of our inferences. In our discussion of the results here, we highlight measures that are significant in terms of the conventional p-values *and* remain significant after multiple-hypothesis corrections.

(1) ***Do children in villages with better infrastructure have smaller learning losses when exposed to floods?*** We find that floods are associated with less learning but that the proximity of the villages to the nearest town is significantly associated with smaller learning losses during floods than in villages that are more distant from the nearest town. We find no evidence that other components of the physical infrastructure are significantly associated on average with different learning losses during floods.

We also find that smaller learning losses are associated with a number of community social infrastructure measures including higher safety from crime, higher educational quality, presence of fair and unbiased teachers, and higher levels of parental-teacher engagement. These findings speak to the large body of literature that documents the positive roles played by strong community social capital, especially during challenging times posed by natural disasters. Our results suggest that in addition to shielding communities from various adversities, community social capital also significantly contributes by at least partially safeguarding children from learning setbacks caused by disruptions to schools and everyday life due to such calamities. Interestingly, one measure that deviates from this pattern is teacher attendance, which is associated with an increase in learning losses. This result, while seemingly surprising, is consistent with the idea that if teacher attendance generally contributes to student learning (as shown by our main effects), and if floods disrupt teacher attendance patterns, then students who normally benefit from high teacher attendance experience larger learning losses during floods. We find no evidence that other components of social infrastructure are significantly associated with different learning losses on average during floods.

(2) ***Are components of infrastructure associated with different learning outcomes for children from more-marginalized versus other groups in the absence of floods?*** Significant coefficient estimates for the "double" interac-

tions, between infrastructure components and marginalization indicators, suggest that in the absence of floods, some infrastructure components are associated with lower learning disparities between marginalized and other children and some components are associated with higher learning disparities between marginalized and other children.

Several key observations are: (i) Most infrastructure components do not significantly affect learning disparities between marginalized and other children. (ii) However, some infrastructure components are significantly associated with learning disparities between these groups even with corrections for multiple hypotheses testing. (iii) Among these, village electrification is associated with greater learning disparities for marginalized children along socioeconomic lines, but lower disparities for girls versus boys. (iv) On the other hand, most social infrastructure components with significant associations, including the presence of more social organizations, conflict-free communities, and communal problem-solving, are associated with lower learning disparities between marginalized and more-privileged children, particularly those whose parents have no schooling. However, there are exceptions where certain social infrastructure components are associated with greater disparities, such as safety against crime for girls versus boys. (v) Impacts of some infrastructure components vary depending on the dimension of marginalization. For example, village electrification is associated with smaller learning gaps for girls versus boys but greater learning gaps for children from poorer versus richer households and for those whose parents have no schooling versus some schooling.

(3) ***Are components of infrastructure associated with smaller learning loss gaps due to floods between children from more- and less-marginalized groups?*** The triple interactions describe how associations of learning losses due to floods differ, or not, for marginalized children relative to other children. We find evidence that some physical and social infrastructure components have different significant associations for children depending on their background.

There are some patterns in these "triple-interaction" estimates (in the presence of floods) that often are similar to but different in some ways from the "double-interaction" estimates (in the absence of floods) for question 2. (i) The majority of the infrastructure components are not associated with significant learning divergences between marginalized and other children in the presence of floods. (ii) Nevertheless, a number of the infrastructure components are associated with significant learning divergences and convergences between marginalized and other children in the presence of floods. (iii) Among these, piped drinking water stands out as the only physical infrastructure component that significantly contributes to the convergence of learning disparities between children of poorer households and those of richer households during floods. (iv) In contrast, among the significant social infrastructure-marginalization interactions, the majority are associated with higher learning losses for marginalized children versus other children in the presence of floods.

Our analyses have limitations. Perhaps most importantly, as in the previous literature, we are unable to control in our estimates the decisions that led to the development of the physical and social infrastructure. So, any interpretations of the significant associations that we present as possibly causal must be qualified. Second, we cannot distinguish between the access and quality of infrastructure measures. The development literature notes that the poor and marginalized often have a weak influence on the actors responsible for the delivery of public goods (Banerjee, Iyer, and Somanathan 2007), which affects the quality and reliability of the services available to them. Third, because of data limitations, we have only been able to consider whether communities had floods between the survey rounds, and not the intensity of exposure in terms of flood frequency within years or duration of each flood.

Notwithstanding these caveats, our analyses have contributed to filling important gaps in the literature on flood-infrastructure interactions and children's learning for the case of rural India. The roles of strong infrastructure in building community resilience and recovery, especially in the context of natural disasters, are well documented. However, our findings suggest that in stratified societies like India, the relationships between infrastructure and flood-related learning losses are complex. We document a few cases where infrastructure improvements can either reduce or increase learning disparities between marginalized and other children, with effects varying by type of infrastructure and dimension of marginalization. These varied findings underscore the need for a nuanced approach to policy interventions that are rooted in local contexts. Such policies must consider the unique challenges faced by different marginalized groups and how various aspects of community infrastructure - both physical and social - interact with these challenges to affect educational resilience. The findings from our analysis of the Indian context also carry an important insight for other stratified societies: in such contexts, the relationships between infrastructure and disaster resilience cannot be understood in isolation from the social structures that determine how different groups access and benefit from community resources.

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Table 1: Descriptive statistics for learning outcomes, flood exposure and community infrastructure measures.

	Mean	Std. Dev.	Min	Max
Learning outcomes				
Math	2.34	0.96	1	4
Reading	3.33	1.42	1	5
Writing	1.68	0.46	1	2
Learning skill	−0.06	0.87	−1.57	1.13
Flood exposure				
Village flood exposure (flooded at least once)	0.33	0.47	0	1
State flood exposure control (% PSUs)	32.32	13.92	3.82	77.78
Physical infrastructure				
Distance to town (km)	14.03	10.51	1	80
Households electrified	0.56	0.36	0	1
Road usable during monsoon	0.75	0.43	0	1
Middle/secondary school	0.66	0.48	0	1
Medical facilities	0.54	0.50	0	1
Primary drinking water source (piped)	0.19	0.33	0	1
Toilet ownership	0.20	0.24	0	1
Social infrastructure				
Communal living arrangement	0.36	0.48	0	1
Social organizations	3.85	2.71	0	12
Safe against crimes	0.94	0.08	0.33	1
Free of conflicts	0.72	0.19	0.15	1
Communal problem solving	0.60	0.31	0	1
Education quality	−0.37	0.89	−2.53	1.44
Teachers are present in school	0.94	0.15	0	1
Teachers seen as fair and unbiased	0.93	0.13	0	1
Teachers don't employ corporal punishment	0.70	0.34	0	1
Teachers are local residents	0.52	0.35	0	1
Parent/household-teacher engagement	0.39	0.34	0	1
Large village	0.79	0.41	0	1

Source: Authors calculations based on Indian Human Development Survey (Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019).
Notes: N= 7250. The sample only includes rural children. All statistics are using attrition weights constructed based on propensity score reweighting.

Table 2: Percentage flood exposed by background characteristics.

Category	**Percentage**	**Number in Category**	**Flood group independence test (χ^2)**
Gender			
Male	32.48	3857	n.s.
Female	34.05	3393	
Child's Age (years)			
Eight	34.80	1707	n.s.
Nine	32.33	1732	
Ten	33.16	2222	
Eleven	32.47	1589	
Caste-religion			
Hindu Upper Castes (UC)	30.04	1149	***
Hindu Marginalized Castes (MC)			
Hindu Other Backward Castes	36.18	2592	
Hindu Scheduled Castes	34.55	1798	
Scheduled Tribes or Indigenous	21.06	723	
Muslim	35.27	900	
Other	11.83	88	
Income Quintiles			
Poor			
First quintile	38.85	1729	***
Second quintile	35.49	1842	
Rich			
Third quintile	32.70	1515	
Fourth quintile	27.43	1181	
Richest	24.31	983	
Parental Education			
Some schooling	31.66	5601	***
No schooling	37.94	1649	

Source: Authors calculations based on Indian Human Development Survey (Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019).
Notes: N= 7250. The sample only includes rural children. All statistics are using attrition weights constructed based on propensity-score reweighting.

Table 3: Coefficient estimates from OLS regressions of learning skills: Main and interaction effects.

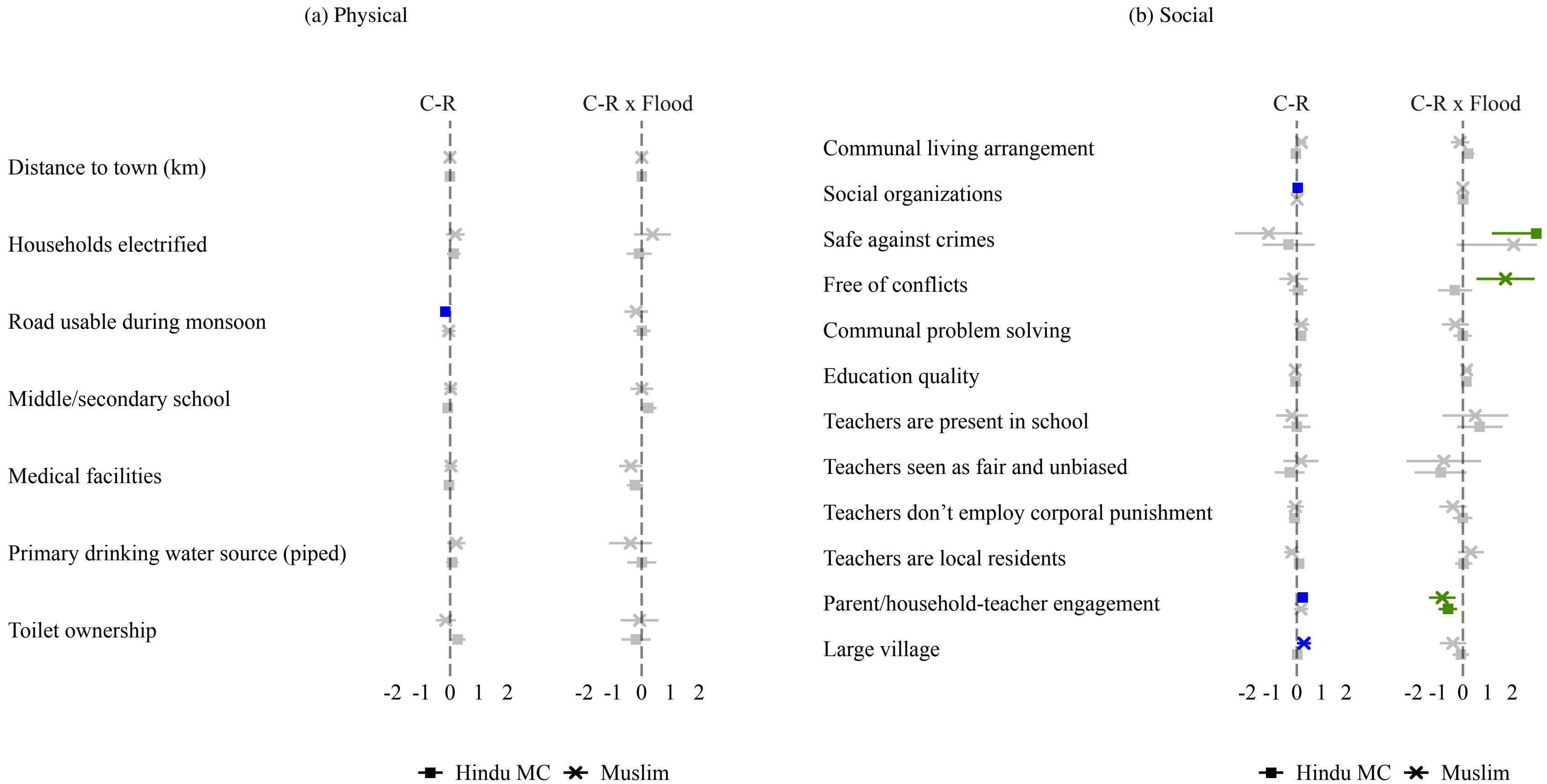
	Only main effects	Main & interaction effects
Flood measures		
Village flood exposure (ref: no floods)	-0.084***‡	-1.383***
	(0.021)	(0.305)
State flood exposure control (% PSUs)	-0.004***‡	-0.003***
	(0.001)	(0.001)
Physical infrastructure		
Distance to town (km)	-0.004***‡	-0.002**
	(0.001)	(0.001)
Households electrified	0.115***‡	0.093**
	(0.032)	(0.040)
Road usable during monsoon	-0.036†	-0.088***
	(0.022)	(0.028)
Middle/secondary school	-0.107***‡	-0.101***
	(0.021)	(0.026)
Medical facilities	0.019	0.027
	(0.021)	(0.025)
Primary drinking water source (piped)	-0.033	0.018
	(0.034)	(0.039)
Toilet ownership	0.246***‡	0.280***
	(0.043)	(0.050)
Social infrastructure		
Communal living arrangement	0.067***†	0.045
	(0.025)	(0.025)
Social organizations (number)	0.002	-0.004
	(0.004)	(0.005)
Safe against crimes	-0.120	-0.514***
	(0.124)	(0.157)
Free of conflicts	0.043	0.081
	(0.052)	(0.062)
Communal problem solving	0.141***‡	0.101***
	(0.030)	(0.037)
Education quality	0.102***‡	0.087***
	(0.011)	(0.014)
Teachers are present in school	0.166**†	0.321***
	(0.068)	(0.084)
Teachers seen as fair and unbiased	-0.001	-0.210**
	(0.077)	(0.094)
Teachers don't employ corporal punishment	-0.070**†	-0.210**
	(0.077)	(0.094)
Teachers are local residents	0.038	-0.063
	(0.032)	(0.041)
Parent/household-teacher engagement	-0.012	-0.063
	(0.028)	(0.041)
Large village (ref: small village)	-0.039	-0.056*
	(0.025)	(0.031)
Infrastructure x Flood interactions		
Physical infrastructure		
Distance to town (km)		-0.005***†

Table 3 continued from previous page

	Only main effects	Main & interaction effects
		(0.002)
Households electrified		0.022
		(0.066)
Road usable during monsoon		0.066
		(0.048)
Middle/secondary school		-0.047
		(0.047)
Medical facilities		-0.007
		(0.045)
Primary drinking water source (piped)		-0.090
		(0.084)
Toilet ownership		-0.126
		(0.091)
Social infrastructure		
Communal living arrangement		0.053
		(0.043)
Social organizations		0.015*
		(0.009)
Safe against crimes		1.032***‡
		(0.261)
Free of conflicts		-0.217*
		(0.118)
Communal problem solving		0.040
		(0.064)
Education quality		0.060**†
		(0.024)
Teachers are present in school		-0.348**†
		(0.151)
Teachers seen as fair and unbiased		0.667***‡
		(0.165)
Teachers don't employ corporal punishment		0.068
		(0.064)
Teachers are local residents		0.070
		(0.058)
Parent/household-teacher engagement		0.132**
		(0.064)
Large village (ref: Small village)		0.097*†
		(0.056)
Constant	-1.830***	-1.352***
	(0.173)	(0.199)
Observations	7250	7250
R2	0.243	0.252
AIC	18925.44	18878.72
BIC	19173.43	19257.6

Source: Authors calculations based on Indian Human Development Survey(Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019). *Notes*: Standard errors in parentheses. All models control for the sex, age, caste-religious group, household income quintiles, and parental education. Coefficients are weighted using attrition weights calculated based on response propensities.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; † $q < 0.10$, ‡ $q < 0.05$.

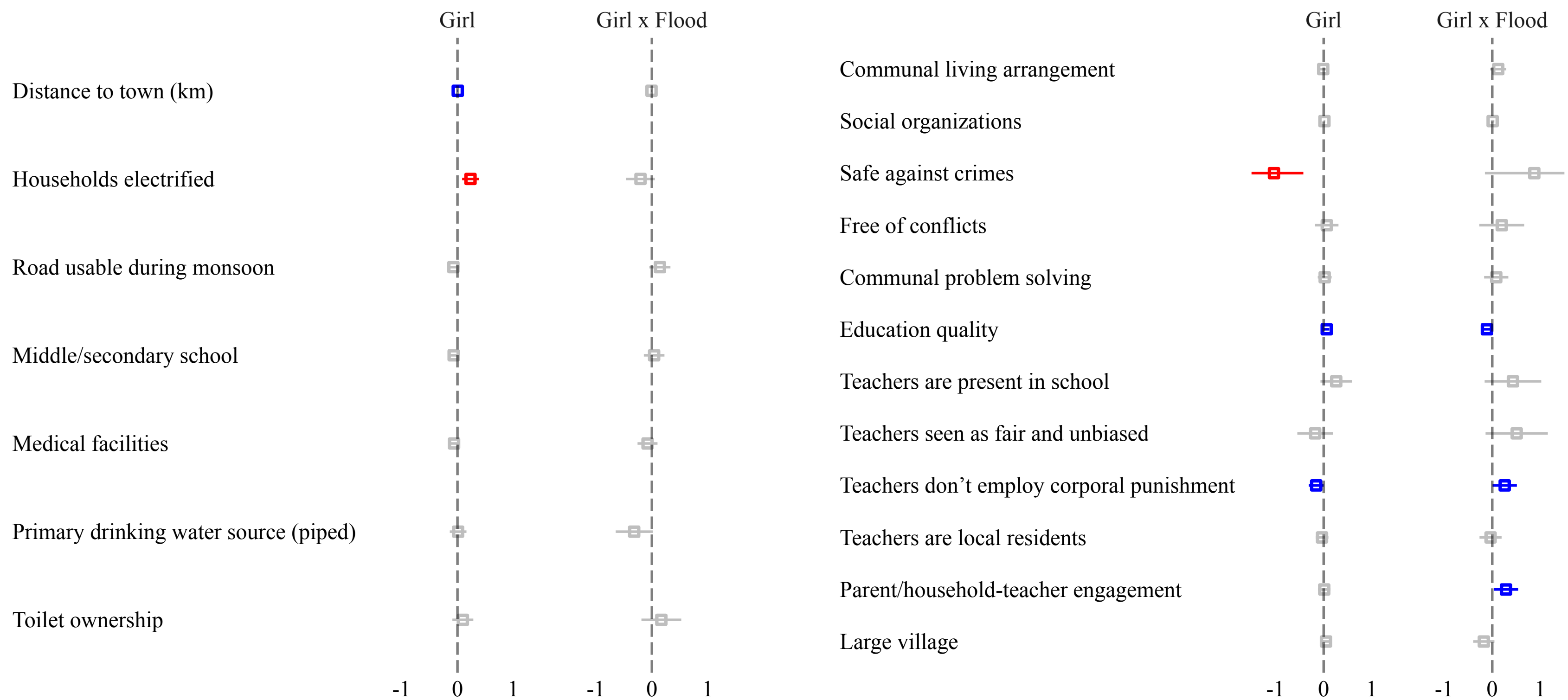
Figure 1: Interaction coefficient estimates for caste-religious groups with community infrastructure (C-R) and with both community infrastructure and flood (C-R x Flood) from OLS regression of learning skills.



Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019).
Notes: N= 7250. The confidence intervals represent 95% confidence levels. The plot indicates significance based on both conventional p-values and FDR q-values. Coefficients shown in color are significant at p-values ≤ 0.05 (red: also significant at q-values ≤ 0.05; green: also significant at q-values ≤ 0.10; blue: not significant by q-values); coefficients not significant are shown in grey. The reference group is privileged Hindu Upper Castes (UC). Hindu MC includes historically marginalized Hindu CastesOther Backward Castes and Scheduled Castesand Scheduled Tribes or Indigenous groups. The OLS model controls for sex, age, household income quintiles, and parental education. The coefficients are weighted using attrition weights calculated based on response propensities. See the full results in Table 2A.

Figure 2: Interaction coefficient estimates for gender with community infrastructure (Girl) and with both community infrastructure and flood (Girl x Flood) from OLS regression of learning skills.

(a) Physical (b) Social

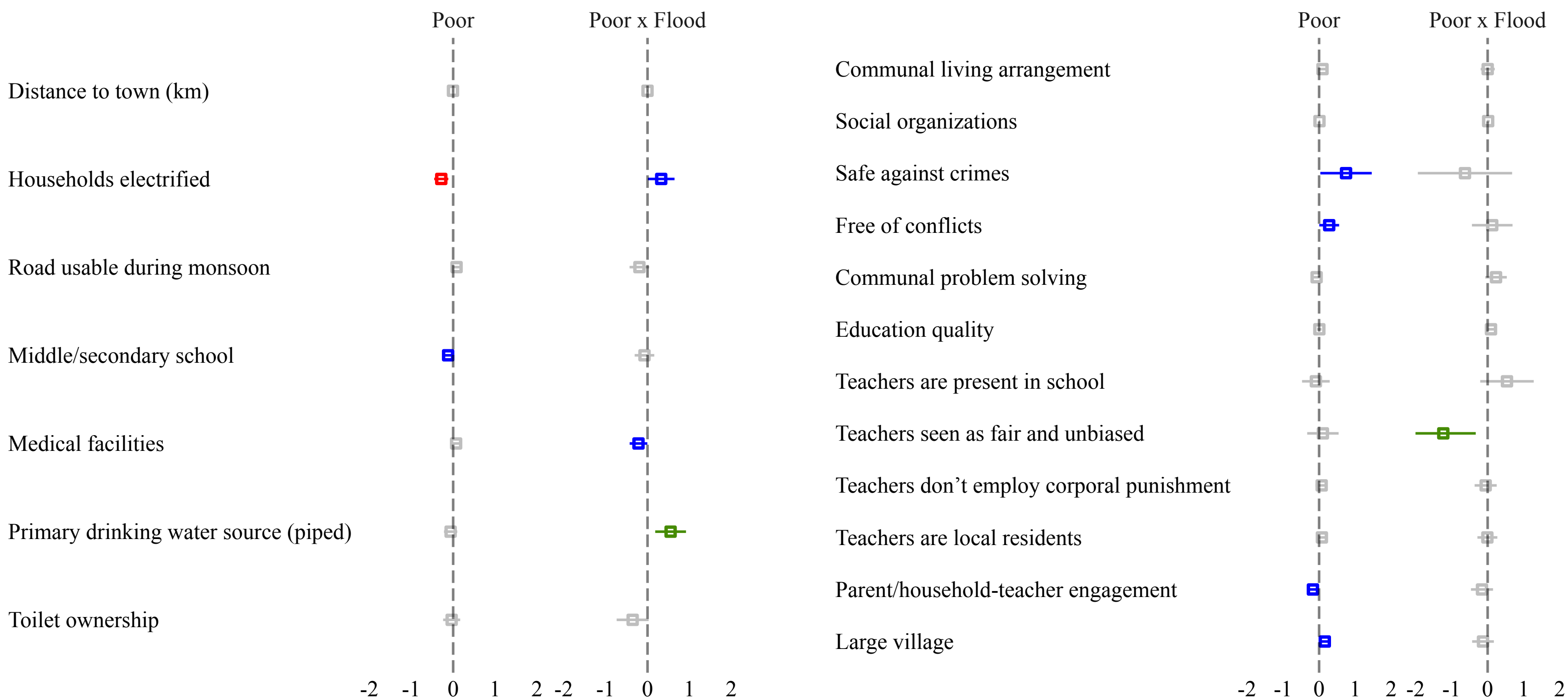


Source: Authors’ calculations based on Indian Human Development Survey (Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019).

Notes: N= 7250. The confidence intervals represent 95% confidence levels. The plot indicates significance based on both conventional p-values and FDR q-values. The coefficients shown in color are significant at p-values $\leq$ 0.05 (red: also significant at q-values $\leq$ 0.05; green: also significant at q-values $\leq$ 0.10; blue: not significant by q-values); coefficients not significant are shown in grey. The reference group is boys. The OLS model controls for age, social group, household income quintiles, and parental education. The coefficients are weighted using attrition weights calculated based on response propensities. See the full results in “Girl (ref: Boy)” in Table 3A.

Figure 3: Interaction coefficient estimates for socioeconomic-income with community infrastructure (Poor) and with both community infrastructure and flood (Poor x Flood) from OLS regression of learning skills.

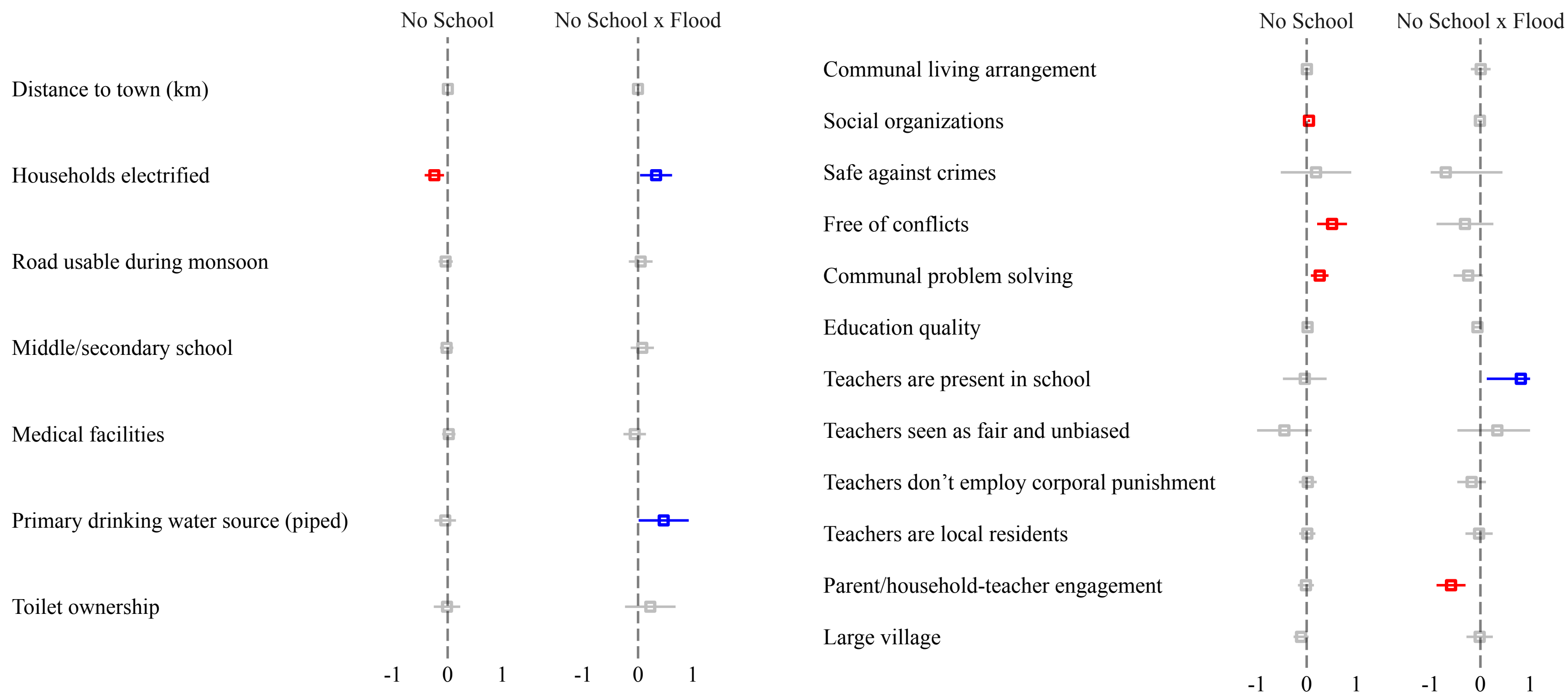
(a) Physical (b) Social



Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019).
Notes: N= 7250. The confidence intervals represent 95% confidence levels. The plot indicates significance based on both conventional p-values and FDR q-values. The coefficients shown in color are significant at p-values ≤ 0.05 (red: also significant at q-values ≤ 0.05; green: also significant at q-values ≤ 0.10; blue: not significant by q-values); coefficients not significant are shown in grey. The reference group is children from rich households. OLS model controls for the sex, age, social group, and parental education. The coefficients are weighted using attrition weights calculated based on response propensities. See the full results in "Poor (ref: Rich)" in Table 3A.

Figure 4: Interaction coefficient estimates for socioeconomic-parental schooling with community infrastructure (No School) and with both community infrastructure and flood (No School x Flood) from OLS regression of learning skills.

(a) Physical (b) Social



Source: Authors' calculations based on Indian Human Development Survey (Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019).

Notes: N= 7250. The confidence intervals represent 95% confidence levels. The plot indicates significance based on both conventional p-values and FDR q-values. The coefficients shown in color are significant at p-values ≤ 0.05 (red: also significant at q-values ≤ 0.05; green: also significant at q-values ≤ 0.10; blue: not significant by q-values); coefficients not significant are shown in grey. The reference group is children whose parents had some schooling. OLS model controls for the sex, age, social group, and household income quintiles. The coefficients are weighted using attrition weights calculated based on response propensities. See the full results under "Parent no school (ref: Some school)" in Table 3A.

A Appendix

Table 1A: Details of the community infrastructure measures.

Category	Question
Physical infrastructure	
Distance to town (km)	How far is that nearest town from here?
Households electrified	About what percentage of the households in the village have electricity?
Road usable during monsoon	Is this road useable during monsoon?
Middle/secondary school	How many government/private middle and secondary school?
Medical facilities	How many government/private health sub-centre/primary health center/community health center?
Primary drinking water source (piped)	What is the main source of water for drinking?
Toilet ownership	Does the household have a toilet of its own? Is there a flush toilet? A latrine? Or any other facility?
Social infrastructure	
Communal living arrangement	In your village do different jatis/groups reside in separate hamlet/mohalla/locality or do they live together?
Social organizations (number)	Are any of these [names of various social, cultural, religious organizations] in the village?
Safe against crimes	A. Now, I would like to ask you some questions about the safety of your village/ neighbourhood: During the last twelve months, (1) was anything stolen that belonged to you or somebody in your household?, (2) did anyone break into your home or illegally get into your home?, (3) did anyone attack you or someone in your household? B.How often are unmarried girls harassed in your village/neighbourhood?
Free of conflicts	(1). In this village/neighbourhood, do people generally get along with each other or is there some conflict or a lot of conflict? (2). In this village/neighbourhood, how much conflict would you say there is among the communities/jatis that live here?
Communal problem solving	In some communities, when there a water supply problem, people bond together to solve the problem. In other communities, people take care of their own families individually. What is your community like?
Education quality	The education quality variable is a constructed measure which represents the standardized average learning skills in a village for the year 2004-05.
Teachers present in school	(1).Is [Was] NAME's class teacher present regularly? (2). Are [Were] most of the teachers at NAME's school present regularly?
Teacher fairness and unbiasedness	(1). 4 Do you think that the class teacher treats [treated] your child in a fair manner? (2). Do you think that the class teacher favours [favoured] certain communities/jatis over others?
Teachers employ corporal punishment	In the last one month, in school has your child been physically beaten/pinched?
Teachers are local residents	Does [Did] NAME's class teacher live in the village/area where the school is?
Parent/household teacher engagement	Do you participate in any school committee like the Parent Teacher Association?
Village size	Village population estimate reported in the village module

Table 2A: Coefficient Estimates from OLS Regressions of Learning Skills: Triple Interaction Models for Caste-religion.

	Hindu MC and Muslims (ref: Hindu UC)
Flood Measures	
Village Flood exposure (ref: no floods)	0.537 (0.931)
State flood exposure (% PSUs)	-0.002* (0.001)
Physical Infrastructure	
Distance to town (km)	-0.0001 (0.003)
Households electrified	-0.010 (0.111)
Road usable during monsoon	0.032 (0.076)
Middle/secondary school	-0.036 (0.067)
Medical facilities	0.044 (0.069)
Primary drinking water source (piped)	-0.044 (0.098)
Toilet ownership	0.111 (0.123)
Social Infrastructure	
Communal living arrangement	0.038 (0.060)
Social organizations (number)	-0.033*** (0.011)
Safe against crimes	0.001 (0.506)
Free of conflicts	0.044 (0.174)
Communal problem solving	-0.055 (0.096)
Education quality	0.137*** (0.038)
Teachers are present in school	0.397 (0.260)
Teachers seen as fair and unbiased	-0.108 (0.282)
Teachers don't employ corporal punishment	-0.005 (0.106)
Teachers are local residents	-0.044 (0.083)
Parent/household-teacher engagement	-0.243*** (0.088)
Large village (ref: Small village)	-0.108 (0.078)
Marginality x Infrastructure interactions	
Physical Infrastructure	
Hindu MC	
Distance to town (km)	-0.002 (0.003)
Households electrified	0.125 (0.119)
Road usable during monsoon	-0.166** (0.083)
Middle/secondary school	-0.090 (0.074)
Medical facilities	-0.038 (0.075)
Primary drinking water source (piped)	0.072 (0.108)
Toilet ownership	0.262* (0.138)
Muslim	
Distance to town (km)	-0.005 (0.005)
Households electrified	0.179 (0.165)
Road usable during monsoon	-0.049 (0.119)
Middle/secondary school	0.018 (0.111)
Medical facilities	0.025 (0.109)
Primary drinking water source (piped)	0.214 (0.162)
Toilet ownership	-0.152 (0.177)
Social Infrastructure	
Hindu MC	

Table 2A continued from previous page

	Hindu MC and Muslims (ref: Hindu UC)
Communal living arrangement	-0.035 (0.066)
Social organizations (number)	0.033*** (0.013)
Safe against crimes	-0.327 (0.536)
Free of conflicts	0.052 (0.188)
Communal problem solving	0.165 (0.106)
Education quality	-0.066 (0.042)
Teachers are present in school	0.002 (0.285)
Teachers seen as fair and unbiased	-0.286 (0.306)
Teachers don't employ corporal punishment	-0.097 (0.115)
Teachers are local residents	0.085 (0.092)
Parent/household-teacher engagement	0.240** (0.096)
Large village (ref: Small village)	0.026 (0.086)
Muslim	
Communal living arrangement	0.187* (0.100)
Social organizations (number)	0.012 (0.020)
Safe against crimes	-1.141 (0.697)
Free of conflicts	-0.128 (0.296)
Communal problem solving	0.188 (0.159)
Education quality	-0.060 (0.052)
Teachers are present in school	-0.196 (0.330)
Teachers seen as fair and unbiased	0.169 (0.361)
Teachers don't employ corporal punishment	-0.059 (0.171)
Teachers are local residents	-0.198 (0.154)
Parent/household-teacher engagement	0.168 (0.145)
Large village (ref: Small village)	0.288** (0.144)
Marginality x Infrastructure x Flood interactions	
Physical Infrastructure	
Hindu MC	
Distance to town (km)	0.003 (0.006)
Households electrified	-0.089 (0.221)
Road usable during monsoon	0.012 (0.155)
Middle/secondary school	0.232 (0.145)
Medical facilities	-0.229 (0.143)
Primary drinking water source (piped)	0.005 (0.259)
Toilet ownership	-0.196 (0.261)
Muslim	
Distance to town (km)	0.003 (0.009)
Households electrified	0.379 (0.327)
Road usable during monsoon	-0.189 (0.209)
Middle/secondary school	0.008 (0.201)
Medical facilities	-0.377* (0.205)
Primary drinking water source (piped)	-0.392 (0.383)
Toilet ownership	-0.072 (0.337)
Social Infrastructure	
Hindu MC	
Communal living arrangement	0.206 (0.133)

Table 2A continued from previous page

	Hindu MC and Muslims (ref: Hindu UC)
Social organizations (number)	0.002 (0.027)
Safe against crimes	2.969***† (0.917)
Free of conflicts	-0.314 (0.355)
Communal problem solving	-0.016 (0.192)
Education quality	0.137* (0.077)
Teachers are present in school	0.681 (0.470)
Teachers seen as fair and unbiased	-0.892* (0.538)
Teachers don't employ corporal punishment	-0.015 (0.202)
Teachers are local residents	0.031 (0.179)
Parent/household-teacher engagement	-0.609***† (0.192)
Large village (ref: Small village)	-0.081 (0.171)
Muslim	
Communal living arrangement	-0.112 (0.191)
Social organizations (number)	-0.004 (0.040)
Safe against crimes	2.056* (1.176)
Free of conflicts	1.724***† (0.600)
Communal problem solving	-0.303 (0.280)
Education quality	0.150 (0.108)
Teachers are present in school	0.502 (0.679)
Teachers seen as fair and unbiased	-0.768 (0.770)
Teachers don't employ corporal punishment	-0.408 (0.282)
Teachers are local residents	0.324 (0.269)
Parent/household-teacher engagement	-0.835***† (0.274)
Large village (ref: Small village)	-0.402 (0.272)
Constant	-1.744*** (0.522)
Observations	7,250
R2	0.261
AIC	18925.44
BIC	19173.43

Source: Authors calculations based on Indian Human Development Survey (Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019).
Note: Standard errors in parentheses. The reference category is Hindu UC. The model controls for age, sex, household income quintiles, parental education, and the interaction between village flood exposure and community infrastructure. Coefficients are weighted using attrition weights calculated based on response propensities.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; † $q < 0.10$, ‡ $q < 0.05$.

Table 3A: Coefficient Estimates from OLS Regressions of Learning Skills: Triple Interaction Models of Infrastructure and Flood Exposure with Child Marginality Status.

	Marginality status		
	Female (ref: Male)	Poor (ref: Rich)	Parent no school (ref: Some school)
Flood measures			
Village Flood exposure (ref: no floods)	-0.371	1.157	-0.092
	(0.444)	(0.749)	(0.719)
State flood exposure (% PSUs)	-0.003***	-0.003***	-0.004*
	(0.001)	(0.001)	(0.002)
Physical infrastructure			
Distance to town (km)	-0.004***	0.001	-0.004***
	(0.001)	(0.002)	(0.001)
Households electrified	-0.009	0.293***	0.172***
	(0.053)	(0.074)	(0.046)
Road usable during monsoon	-0.044	-0.138***	-0.068**
	(0.039)	(0.053)	(0.033)
Middle/secondary school	-0.069**	-0.017	-0.085***
	(0.035)	(0.048)	(0.030)
Medical facilities	0.057	-0.013	0.020
	(0.035)	(0.047)	(0.029)
Primary drinking water source (piped)	0.003	0.052	0.043
	(0.054)	(0.066)	(0.044)
Toilet ownership	0.228***	0.315***	0.372***
	(0.066)	(0.086)	(0.057)
Social infrastructure			
Communal living arrangement	0.043	-0.010	0.053*
	(0.034)	(0.044)	(0.028)
Social organizations (number)	-0.011*	-0.012	-0.006
	(0.007)	(0.008)	(0.005)
Safe against crimes	0.011	-0.954***	-0.482***
	(0.222)	(0.316)	(0.187)
Free of conflicts	0.060	-0.065	-0.040
	(0.084)	(0.118)	(0.072)
Communal problem solving	0.092*	0.178***	0.082*
	(0.051)	(0.068)	(0.043)
Education quality	0.064***	0.081***	0.090***
	(0.019)	(0.027)	(0.016)
Teachers are present in school	0.196	0.451***	0.375***
	(0.121)	(0.170)	(0.094)
Teachers seen as fair and unbiased	-0.143	-0.316	-0.130
	(0.132)	(0.194)	(0.104)
Teachers don't employ corporal punishment	0.007	-0.115	-0.037
	(0.054)	(0.072)	(0.048)
Teachers are local residents	0.021	-0.042	0.013
	(0.046)	(0.062)	(0.039)
Parent/household-teacher engagement	-0.064	0.077	-0.021
	(0.046)	(0.062)	(0.039)
Large village (ref: Small village)	-0.080*	-0.160***	-0.044
	(0.042)	(0.057)	(0.035)
Marginality status x Infrastructure interactions			
Physical infrastructure			

Table 3A continued from previous page

	Marginality status		
	Female (ref: Male)	Poor (ref: Rich)	Parent no school (ref: some school)
Distance to town (km)	0.005**	-0.004*	0.003
	(0.002)	(0.002)	(0.002)
Households electrified	0.233***‡	-0.284***‡	-0.243***‡
	(0.076)	(0.086)	(0.090)
Road usable during monsoon	-0.073	0.081	-0.037
	(0.056)	(0.063)	(0.066)
Middle/secondary school	-0.068	-0.120**	-0.019
	(0.051)	(0.057)	(0.062)
Medical facilities	-0.061	0.070	0.020
	(0.050)	(0.056)	(0.062)
Primary drinking water source (piped)	0.012	-0.060	-0.045
	(0.076)	(0.081)	(0.100)
Toilet ownership	0.096	-0.036	-0.012
	(0.095)	(0.104)	(0.123)
Social infrastructure			
Communal living arrangement	-0.009	0.094*	0.004
	(0.049)	(0.053)	(0.062)
Social organizations (number)	0.016*	0.010	0.046***‡
	(0.010)	(0.010)	(0.013)
Safe against crimes	-1.033***‡	0.747**	0.188
	(0.312)	(0.364)	(0.362)
Free of conflicts	0.065	0.280**	0.511***‡
	(0.124)	(0.141)	(0.153)
Communal problem solving	0.021	-0.069	0.262***‡
	(0.073)	(0.081)	(0.091)
Education quality	0.063*	0.007	0.018
	(0.027)	(0.031)	(0.031)
Teachers are present in school	0.261	-0.090	-0.038
	(0.167)	(0.196)	(0.225)
Teachers seen as fair and unbiased	-0.177	0.105	-0.449
	(0.189)	(0.222)	(0.280)
Teachers don't employ corporal punishment	-0.156**	0.071	0.023
	(0.079)	(0.086)	(0.092)
Teachers are local residents	-0.034	0.077	0.012
	(0.068)	(0.074)	(0.083)
Parent/household-teacher engagement	0.012	-0.171**	-0.015
	(0.067)	(0.074)	(0.082)
Large village (ref: Small village)	0.048	0.158**	-0.113
	(0.061)	(0.068)	(0.077)
Marginality status x Infrastructure x Flood interactions			
Physical infrastructure			
Distance to town (km)	-0.007*	-0.0003	-0.002
	(0.004)	(0.005)	(0.005)
Households electrified	-0.204	0.326**	0.329**
	(0.131)	(0.162)	(0.149)
Road usable during monsoon	0.143	-0.194	0.048
	(0.096)	(0.120)	(0.111)
Middle/secondary school	0.040	-0.073	0.077

Table 3A continued from previous page

	Marginality status		
	Female (ref: Male)	Poor (ref: Rich)	Parent no school (ref: some school)
	(0.094)	(0.119)	(0.108)
Medical facilities	-0.078	-0.215**	-0.062
	(0.091)	(0.107)	(0.105)
Primary drinking water source (piped)	-0.316*	0.550***†	0.468**
	(0.169)	(0.187)	(0.233)
Toilet ownership	0.169	-0.355*	0.223
	(0.182)	(0.195)	(0.235)
Social infrastructure			
Communal living arrangement	0.124	0.001	0.007
	(0.085)	(0.100)	(0.102)
Social organizations (number)	0.008	0.014	-0.010
	(0.018)	(0.020)	(0.023)
Safe against crimes	0.874*	-0.629	-0.697
	(0.524)	(0.667)	(0.582)
Free of conflicts	0.197	0.127	-0.311
	(0.238)	(0.287)	(0.292)
Communal problem solving	0.083	0.232	-0.246
	(0.128)	(0.152)	(0.151)
Education quality	-0.111*	0.093	-0.059
	(0.049)	(0.064)	(0.054)
Teachers are present in school	0.430	0.536	0.814*
	(0.300)	(0.378)	(0.350)
Teachers seen as fair and unbiased	0.508	-1.230***†	0.340
	(0.330)	(0.459)	(0.410)
Teachers don't employ corporal punishment	0.259*	-0.055	-0.177
	(0.129)	(0.156)	(0.147)
Teachers are local residents	-0.035	-0.008	-0.027
	(0.117)	(0.141)	(0.140)
Parent/household-teacher engagement	0.286*	-0.157	-0.591***‡
	(0.129)	(0.156)	(0.149)
Large village (ref: Small village)	-0.176	-0.129	-0.015
	(0.113)	(0.154)	(0.135)
Constant	-1.757***	-0.920***	-1.177***
	(0.263)	(0.334)	(0.221)
Observations	7,250	7,250	7,250
R2	0.263	0.263	0.233
AIC	18925.44	18925.44	18925.44
BIC	19173.43	19173.43	19173.43

Source: Authors calculations based on Indian Human Development Survey (Desai, Vanneman, and National Council of Applied Economic Research, New Delhi 2019).
Note: Standard errors in parentheses. All models control for age and the interaction between village flood exposure and community infrastructure. The "Female" model controls for age, caste-religious group, household income quintiles, and parental education. The "Poor" model controls for age, sex, caste-religious group, and parental education. The "No school" model controls for age, sex, household income quintiles, and caste-religious group. Coefficients are weighted using attrition weights calculated based on response propensities.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; † $q < 0.10$, ‡ $q < 0.05$.