Are Natural Disasters Disastrous for Education? Evidence from Seven Asian Countries

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Abstract

We estimate the impact of natural disasters on children's educational outcomes in seven countries across Asia and the Pacific—the world's most disaster-prone region. Linking novel survey data on children aged 5 to 17 years to time- and geo-coded disaster records, we construct time-varying disaster exposure measures for the first 1,000 days from conception, the most recent years, and the period in between. We analyze exposures to several types of disasters—all disasters, floods, and severe disasters. We find significant negative effects of early-life disaster exposure on school enrollment, while recent disasters show weaker or no corresponding effects when all disasters are considered. The impact of recent disaster exposure on math-test scores is limited, while early-life exposure shows persistent negative effects. The results reveal important heterogeneities with policy implications. Negative enrollment effects are more pronounced for both girls and boys at upper-primary and middle-school ages, with variation across disaster types. No substantial gender differences are observed in math performance effects, although effects differ by region. Interestingly, enrollment among younger children may increase following recent disasters, though this pattern is limited to certain disaster types and regions.

Keywords: Educational economics, natural disasters, human capital, learning outcomes

JEL: I24, I25, Q54, Q56

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1 Introduction

The United Nations reports that between 1970 and 2019, climatic change and extreme weather caused a surge in natural disasters. Natural hazards accounted for 50% of all disasters, 45% of all reported deaths, and 74% of all reported economic losses (United Nations 2021). In the coming decades, climatic change will continue to lead to the increased frequency and severity of natural disasters such as floods, droughts, and extreme weather (Intergovernmental Panel on Climate Change 2022). Asia and the Pacific is particularly under the threat as the worlds' most natural-disaster-prone region. For example, in 2022, over 140 disasters struck Asia and the Pacific, causing over 7,500 deaths, affecting over 64 million people, and causing economic damage estimated at $57 billion (UN-ESCAP 2023).

Children are widely exposed to natural disasters. Approximately one billion children across the world, many living in countries with poor access to essential services, are at an "extremely high risk" of experiencing impacts of the climatic crisis (UNICEF 2021b). The impacts of climatic disasters on children's education are multifaceted. Natural-disaster shocks may impact children's learning processes through schooling disruptions. Or, schools might be potential places of refuge for children in settings where school facilities might be more resilient than homes and if parents are unable to provide their usual care for children at home after disasters strike (e.g., when their houses are destroyed or inundated). For example, in 2010 in Pakistan, 11,906 schools with more than one million children were affected by natural disasters due to schools experiencing disaster-induced damage (9,232), as well as the usage of schools as post-disaster shelters (2,674) (Chang et al. 2013).[1] In addition to their effects on school operations, disasters can lead to negative income shocks. They can reduce household resource availability for schooling, and increase the opportunity costs of schooling as children compensate for lost parental income by taking up greater household and wage-work responsibilities (Alam 2015; Bandara, Dehejia, and Lavie-Rouse 2015; Cas et al. 2014; Guarcello, Mealli, and Rosati 2010; Rosales-Rueda 2018). On the other hand, they can lead to health shocks, such as causing unanticipated parental deaths and reducing children's physical capacity to attend school. Exposure to natural disasters prenatally through early life has been linked to worse short- and long-run health outcomes (Almond and Mazumder 2005; Lin and Liu 2014; Ciancio et al. 2023; Gunnsteinsson et al. 2015; Liu, Liu, and Tseng 2022; Rondó et al. 2003; Sable and Wilkinson 2000; Torche 2011). Exposures could also raise the cost of attending schools, compared to costs for healthier peers, if exposure impacts create the need for more specialized education and more medical attention, and if exposed children are more likely to miss classes.

In this paper, we provide to our knowledge the first cross-country and all-natural-disaster-inclusive analyses of the effects of disruptive natural disasters on human-capital accumulation, taking into consideration each child's individual-specific history of disaster exposures. We link individual-level information on children aged 5 to 17 from seven developing countries in Asia from the Multiple Indicator Cluster Surveys (MICS) (UNICEF 2010) with time- and geo-coded

1. The impact of disruptions on school attendance and how to strengthen the resilience of school systems has garnered significant attention, particularly in the wake of the COVID-19 pandemic (Angrist et al. 2023; McCoy et al. 2021; UNICEF 2021a). In this paper, we focus on the arguably "more-normal" pre-COVID period and do not study the effects of the COVID-19 pandemic on educational outcomes.

disaster variables from the Emergency Events Database (EM-DAT) (Delforge et al. 2023). Given the countries and ages of children in the sample, we link 355 natural disasters that have led to a substantial loss of human life in these countries between 1999 and 2019 from EM-DAT. These disasters include floods, storms, droughts, earthquakes, and extreme temperature events.[2] We construct a novel dataset that provides time-, age-, and location-specific disaster exposure histories for children. To identify causal effects, we exploit the structure of the MICS survey design, which includes multiple subnational locations surveyed at different times. Our identification strategy compares successive birth cohorts of children within the same subnational units, leveraging variation in the timing of disasters relative to children's ages and the timing of the surveys. By focusing on within-location variation in exposure across cohorts and controlling for relevant covariates, we isolate the effects of children's disaster exposure from time-invariant location characteristics and broader national trends.

The short-term effects of disasters on enrollment and cognitive skills could lead to long-term impacts on human-capital development and accumulation. Therefore, we focus on not only the impacts of recent disasters but also those of early life disasters on human-capital accumulation. Due to negative health and economic impacts, for example, changes in prenatal stress caused by natural-disaster exposures have negative impacts on educational and economic performance later in life (Andrabi, Daniels, and Das 2021; Charil et al. 2010; Fuller 2014). Central-nervous systems and brains undergo rapid growth between 8 and 25 weeks post-conception—a process that is essential for cognitive development and performance (Almond, Edlund, and Palme 2009). Therefore, we focus on the period from conception until age two (the first 1,000 days) to construct early life shocks.[3] In our first empirical model, we estimate the impacts of disasters on the enrollment status of children. Specifically, we implement an equation that treats the current enrollment status, during the month of the survey, as a function of prior attainment, prior enrollment, and parental characteristics, along with children's recent and earlier disaster-exposure histories. In our second empirical model, we specify an important indicator of learning—MICS-administered math-test scores—as the output of a human-capital-production function (Todd and Wolpin 2003; Hanushek and Rivkin 2012). In particular, we divide a child's disaster history into three periods: the first 1,000 days, the time between the first 1,000 days and the most recent two years, and the most recent two years.

We find significant negative effects of early life disaster exposure on school enrollment across various types of disasters, whereas recent disaster events are associated with weaker or no effects. Heterogeneity analyses show that, when considering all disasters recoded in EM-DAT, boys experience persistent negative impacts from early-life disaster exposure on enrollment throughout primary-school ages, while the effects for girls are comparatively weaker. In the case of floods, children of both genders are negatively affected, particularly as they reach upper-primary and secondary-school ages. Interestingly, enrollment among younger children may

2. In addition to considering all EM-DAT natural disasters, we also show results considering only floods, only severe disasters, and only severe floods. Severe disasters are defined as causing more than 500 deaths or injuries or affecting at least 5,000 people.

3. The first 1,000 days have been strongly emphasized in the literature on nutrition, as well as other dimensions of child development (Behrman 2015; Doyle 2020; Grantham-McGregor et al. 2007; Hoddinott et al. 2008; Hoddinott et al. 2013; Gertler et al. 2014; Black et al. 2022; Victora et al. 2008; Victora et al. 2010).

increase following recent severe disaster shocks, although this pattern is limited to certain disaster types and regions. The impact of recent disaster exposure on math test scores is generally limited, although it varies slightly across disaster types. However, negative impacts from early-life disaster exposure on math test scores observed for both boys and girls. It is important to note that these findings are based on children who survived natural disasters. Given this positive selection, the estimated negative effects of children's disaster exposure on educational outcomes are likely to be underestimated.

This paper contributes to the literature in the following ways. First, we consider the exposure history to multiple natural disasters for children, capturing both early life and recent shocks, and estimate the longer-term effects of early life exposure to natural disasters on educational outcomes. While prior studies have examined how disasters affect children, relatively fewer studies investigate the impacts of disasters on educational outcomes and most focus on the impacts of single large-scale events (Cho and Kim 2023; Hadiman and Djamaluddin 2022; Tian, Gong, and Zhai 2022; Ciraudo 2020; Gibbs et al. 2019; De Vreyer, Guilbert, and Mesple-Somps 2015; Cas et al. 2014). They usually examine one disaster in one country rather than multiple types of disasters in multiple countries.[4] Examples include a study showing the negative impact of the 2017 Pohang earthquake in the Republic of Korea on college-entrance-exam scores (Cho and Kim 2023), a study showing that lower adult-educational attainment was linked to high-intensity exposure to the 1976 Tangshan earthquake in the People's Republic of China (Tian, Gong, and Zhai 2022), a study revealing lower cognitive scores for children aged 0–2 who experienced the 2006 Yogyakarta earthquake in Indonesia (Hadiman and Djamaluddin 2022), and a study showing Jamaican girls' school attendance in rural areas decreased in the short-to-medium term after Hurricane Ivan in 2004 driven by school damages (Raeburn 2023). Ciraudo (2020) tracks the academic performance of a cohort in Chile affected in early life by the 1985 earthquake, and De Vreyer, Guilbert, and Mesple-Somps (2015) shows negative educational outcomes after large income shocks related to the 1987–89 locust plague in Mali. Gibbs et al. (2019) finds that academic performance was reduced in schools with higher exposure to a major bushfire in Australia. Cas et al. (2014) studies the effects of the 2004 Indian Ocean tsunami on school attendance and time allocation in the short run, as well as educational trajectories and marriage in the long run.

Second, we explore the heterogeneity globally and locally with a large sample. Our findings contribute to the existing literature showing that impacts in early life have a gender-and-age-differentiated long-term reach. A group of studies for developing countries have found that the negative impacts of shocks are stronger for girls than for boys in the short run in terms of mortality rates (Gupta 1987; Rose 1999; Jayachandran 2009), educational expenses (Thomas

4. There are a limited number of studies on broad groups of disasters. Those using multiple types or groups of disasters, however, do not focus on educational outcomes in developing countries. Opper, Park, and Husted (2023) use data from the US and find that natural disasters affect a region's human capital via both reductions in learning for students who stay in school and grade completion in school. Simeonova (2011) also uses US data and Currie and Rossin-Slater (2013) study the impact of hurricanes in Texas, but both studies concentrate on pregnancy and birth outcomes. Caruso (2017) examines the long-term effects of exposures to multiple natural disasters on educational attainment and labor-market outcomes in Latin America, as well as the intergenerational transmission of early life exposures. Our paper, in contrast, emphasizes the educational outcomes of children directly exposed to disasters, examining both enrollments and foundational learning outcomes assessed using survey-administered math-test scores, which provide a valuable measure of cognitive skills.

et al. 2004; Cameron and Worswick 2001), and cognitive development (Chang, Favara, and Novella 2022; Nübler et al. 2021). This may be due to households prioritizing boys' welfare (Drèze and Sen 1991), as well as gendered differences in medical care and nutritional allocations (Alderman and Gertler 1997; Behrman 1988; Behrman and Deolalikar 1990; Gupta 1987). However, a competing narrative around likely disaster impacts on gender disparities also exists. As child farm laborers are mostly boys, when disaster strikes, there may be disadvantage towards boys' education, especially the older ones as "school dropout and child labor as self-insurance" (Takasaki 2017; Wu, Lin, and Han 2023).

The rest of this paper is organized as follows. Section 2 describes the data and construction of key measures. Section 3 presents summary statistics. Section 4 describes the estimation strategy separately for enrollment status and math-test scores. Section 5 presents and interprets the main results. Section 6 concludes the paper. Tables and figures that are referenced with a capital-letter prefix are in the Online Appendix.

2 Data

2.1 Data on Educational Outcomes

We use MICS6, the 6th round of the Multiple Indicator Cluster Survey (UNICEF 2010), to study the effects of natural disasters on educational outcomes. MICS is a global multi-purpose survey program conducted by the United Nations Children's Fund (UNICEF) that provides statistically robust and internationally comparable data on the situation of children and women. From the mid-1990s until 2024, it has covered 121 countries with 365 surveys containing more than 30 Sustainable Development Goals (SDGs) indicators. It has served as an integral part of the information for the plans and policies of many governments and is one of the two largest household-survey programs in low- and middle-income countries (Amouzou et al. 2017).

MICS surveys are cross-sectional and use multistage probability designs. They are representative at national and sub-national levels. In each round, MICS provides nearly uniform data collection instructions and survey questions across survey countries. The household and individual questionnaire modules are administered by interviewers to women and men aged 15 to 49 years, to mothers or caretakers of all children under 5 years of age, and to one randomly selected child aged 5–17 years in the household. The growing literature using MICS highlights its value as a good resource for multicountry- or sub-national-level analysis. Recent rounds, for example, have been used to study the effects of COVID-19 school closures on cognitive skills (Alban Conto et al. 2021; McCoy et al. 2021).

The unit of analysis in this paper is the individual child. MICS6 provides information on school enrollments for children aged 5 to 17 and on foundational math learning for a subset of these children aged 7 to 14, which constitute our two dependent variables.[5] MICS6 also offers information on child characteristics (e.g., gender, age, schooling attainment prior to the surveys) and household characteristics (parental age and schooling attainment, household income), which we use as controls and to explore heterogeneous effects. Overall, we use information from the Household, Individual, and Children Aged 5 to 17 questionnaires of MICS6.

5. Foundational math learning is not available in previous rounds of MICS.

We focus on low- and middle-income Asian countries whose MICS6 data were collected pre-pandemic. These include countries in South Asia (Bangladesh 2019, Nepal 2019, Pakistan 2017–2019), East and Southeast Asia (Mongolia 2018, Thailand 2019), and Central Asia (Kyrgyz Republic 2018, Turkmenistan 2019).[6]

2.2 Data on Disasters

Our natural-disaster variables are constructed from the EM-DAT database (1900–2023) (Delforge et al. 2023). Each disaster event is recorded with its start and end dates, along with a list of affected locations. This allows us to match individuals in MICS6 with disaster events based on location and month, enabling the construction of disaster-exposure measures.

EM-DAT is an international database compiled by the Centre for Research on the Epidemiology of Disaster (CRED) with comprehensive information on natural disasters that cause substantial losses of human life. These disasters encompass geophysical, meteorological, hydrological, climatological, or biological events. It is compiled from various sources: UN agencies, non-governmental organizations, insurance companies, research institutes, and press agencies. A disaster is recorded in EM-DAT if it meets at least one of the following criteria: (a) 10 or more people killed, (b) 100 or more people affected, (c) declaration of a state of emergency, or (d) a call for international assistance (Panwar and Sen 2020; Mavhura and Raj Aryal 2023; Sy et al. 2019).

EM-DAT is the most widely employed resource for studying the impacts of disaster shocks on long-term multi-dimensional economic outcomes such as GDP growth (Botzen, Deschenes, and Sanders 2019; Klomp and Valckx 2014). A meta-analysis of disaster-focused macroeconomic literature concludes that more than 60% of the 64 primary studies published in 2000–2013 used EM-DAT (Lazzaroni and Bergeijk 2014). Globally, it is used to analyze whether economic development mitigates natural disasters' effects on death (Kahn 2005), to study the correlation between natural disasters and economic growth (Skidmore and Toya 2002), and to investigate if high-quality institutions mitigate the effects of disasters on short- and long-run growth (Felbermayr and Gröschl 2014; Noy 2009). The effects of disasters on firm-level outcomes including employment, asset accumulation, and productivity are examined using a panel of data from European firms and EM-DAT (Leiter, Oberhofer, and Raschky 2009). Given the recording of various types of disasters in EM-DAT, researchers are able to aggregate different disasters occurring in certain locations and time spans into a single index (Botzen, Deschenes, and Sanders 2019). EM-DAT has also been combined with alternative national-administrative sources on disasters to classify disasters by fatalities (Boustan et al. 2020).

The available EM-DAT variables can be categorized into two groups: context variables and impact variables. Context variables provide temporal and geographical information for disasters and impact variables measure the human and economic impacts of disasters. Temporal information includes the start date and end date of each disaster. Geographical variables include the administrative level and name of all locations affected by each disaster. The administrative level at which information is available varies by country. For example, in Bangladesh, we know

6. For example, MICS6 for Viet Nam started in 2020 and continued in 2021, so we do not include these data in this study to avoid confounding effects due to the pandemic.

which states or districts a disaster impacts—which can be matched to MICS6 information on the districts in which children reside. Districts are the second-level administrative divisions in Bangladesh, with populations ranging from under 700,000 in places like Rangamati to over 14,700,000 in Dhaka.

Impact variables assess the severity of each disaster. We jointly use the number of casualties and the number of individuals impacted by each disaster to classify the severity of disasters. While EM-DAT disaster records also include data on the economic damage of disasters, we do not use these variables due to the relatively limited availability.

2.3 Measures

2.3.1 Parental and Household Characteristics

For socioeconomic status (SES), we consider the parents' schooling levels, whether the parents are alive, and whether the parents reside with the children. MICS conducted interviews with all women and men in selected households aged 15 to 49 while also gathering key information about all household members. We obtain the information of mother and father from the household modules.[7] We construct two measures for parental educational attainment: the first is an indicator for having ever attended school, and the second is an indicator for having achieved secondary education.

2.3.2 Educational Variables

The educational variables include school enrollments and attainment for children aged 5 to 17 and math-learning skills for children aged 7 to 14. Enrollments and math-learning skills are the outcomes considered.[8] "Ever enrolled", "Enrollment in last school year t-1", and "Enrollment in current school year t" are dummy variables constructed from survey questions "Has (name) ever attended school or any Early Childhood Education programme?", "At any time during the previous school year did (name) attend school or any early childhood education programme?", and "At any time during the current school year did (name) attend school or any Early Childhood Education programme?", respectively.

Math skills are assessed for children aged 7 to 14 by tests administered in the survey. Since these tests are administered at the children's homes, assessments are collected regardless of the children's school-enrollment status, thus avoiding the selectivity bias that would occur if the tests were administered only to those attending schools. The math test in MICS is included in the Foundational Learning Skills (FLS) module, designed to monitor the learning outcomes at the grade 2 or 3 level (Gochyyev, Mizunoya, and Cardoso 2019). These tests are uniform regardless of countries and regions. The overall math score is aggregated from scores on test components on recognizing symbols, comparing numbers, adding numbers, and identifying the next number. MICS6 also asks "which level and grade or year is (name) attending?" during "the previous school year" and "this current school year", as well as "Did (name) ever complete that

7. The parents are either the biological parents or caregivers in the households.

8. We provide more details on the construction of measures in the Online Appendix. MICS conducts reading assessments as well, but the sample coverage is only 60% and there are complications due to different lanuages used, so we do not investigate reading scores in this paper.

(grade/year)?". To have uniform cross-country comparable attainment measures, we calculate the grades of schooling completed from the above information as "Attainment at start of last school year t-1" and "Attainment at start of current school year t". Using the survey question "What is the highest level and grade or year of school (name) has ever attended?", we construct the variable "Attainment (highest)" with the same logic. The average enrollment rates, math scores, and attainments for the whole sample are shown in Table 2.

2.3.3 Disaster Shocks

Location and Migration. We identify disaster at the finest available administrative level for each country as shown in Table 1. Correspondingly, we assume that children have resided since conception within these administrative units (e.g., district in Bangladesh and changwat in Thailand).

While the migration history of children is not observed, it is feasible to identify some of the biological mothers of the children in our sample from the eligible-women-survey module to extract the migratory history utilizing one main piece of information: years living in the current city, town, or village.[9] These locations of residence are at a much lower administrative unit then our MICS administrative units of districts, regions, and changwats.

Maternal location information is not available for all children in our sample. First, the Pakistan Khyber Pakhtunkhwa Province (denoted as "PKK") women module does not contain migration variables and 13.4% of children in our sample come from this province. Second, only women aged 15 to 49 are surveyed in the women's module, while some natural mothers of children in the sample may be older. Approximately 81% of children have mothers whose ages fall within the 15 to 49 age range. Hence, among the 144,471 children in our full sample, 43,036 (30%) children could not be matched with any woman aged 15 to 49, and 45,952 (32%) children could not be matched with information on the maternal duration of residency in the current location.[10]

Among the sample for which we do have linked-maternal migration information, we find that, across countries and on average, mothers have resided at their current city, town, or village for 92% to 98% of the years since the birth of their child selected for the 5-to-17 Child Questionnaire. Furthermore, across countries and on average, between 83% and 96% of the

9. We use this question from MICS6 survey for individual women to obtain information on mothers' migration history: WB 15. How long have you been continuously living in (name of current city, town or village of residence)? The answer records the number of years they have been living in the same city, town, or village, which are divisions finer than the districts or regions. We use this number of years, interview year, and children's birth year, to conclude if mother has been always residing in the same location since the conception of children. Although MICS6 also asks "Before you moved here, in which region did you live in?", they do not record how long the respondents have lived in the prior location. Additionally, prior location name might be recorded at a different administrative level.

10. MICS has several modules. The "Household Module" collects basic demographic characteristics such as education, age, and gender of every household member, and their relationships with the household head. The "Children Age 5-17 Module" is the one on children from which we obtain individual information as well as educational outcomes. The "Individual Women Module" collects more-detailed data on individual women aged 15-49 years. We obtain all the measures on children's parents from the "Household Module" and do not impute the missingness. For example, in Table 2. Summary statistics for all children, 144,338 out of 144,471 children are observed with the information on "Mother ever educated (dummy)" in the raw data. However, for migration information, we need to match the children with women in the "Individual Women Module" as the "duration of residence" is collected in this module only.

mothers have not moved from their city, town, or village since the birth of their child selected for the 5-to-17 Child Questionnaire. It is likely that among the limited share of mothers who have moved, a large portion moved within our disaster-linked MICS administrative units. The MICS administrative units are first-level and second-level administrative divisions that are large in each country and most migrations are likely within these divisions in our empirical setting (Bangladesh Bureau of Statistics (BBS) and UNICEF Bangladesh 2019; Bureau of Statistics 2021). Given these patterns, our locational histories, constructed under the assumption that children have not moved out of disaster-linked MICS administrative units since conception, capture fairly well the actual locational histories of children in our sample.

Binary and Continuous Measures of Disaster Intensity in Particular Time Spans. In EM-DAT, all locations in first-level and second-level administrative divisions affected by one disaster are listed. As we also observe either first-level or second-level administrative locations of individuals in MICS, we are able to link disasters with each location in the MICS data. For example, Chandpur District is one district in Chittagong Division in Bangladesh. If a flood event is recorded as having affected Chittagong Division at a given time in EM-DAT, then children in Chandpur District at that time are assumed to be exposed to this flood.

Jointly, by using the birth year-month, interview year-month, disaster start year-month and end year-month, and child and disaster locations from MICS6 and EM-DAT, we match disasters to each child and generate a child-level monthly panel dataset that records for each child at each age-in-months whether a disaster occurred in the administrative unit in which the child resides and the characteristics of the disaster. Specifically, in this child-monthly panel, we have a binary indicator of disaster, DI^p_{ilg}, which equals one if a type-p-intensity disaster (see discussion below) took place in location l when child i—who resides in l—was g months of age and zero otherwise.

We divide a child's life into segments indexed by j and define FM_{ij} and LM_{ij} as the child-specific first and last age-in-months for each time segment j.[11] To analyze child-disaster exposure within each time segment j, we aggregate over DI^p_{ilg} to generate

$$\begin{gathered} DM^p_{ilj} = \sum_{g=FM_{ij}}^{LM_{ij}} DI^p_{ilg} \\ \text{and } DB^p_{ilj} = 1\{DM^p_{ilj} \geq 1\} \ . \end{gathered} \tag{1}$$

DM^p_{ilj} captures the number of months child i in location l experiences a disaster of type p during time segment j, and DB^p_{ilj} indicates if the child experiences a type-p disaster during any month in time segment j.

Critical Life-Cycle Periods. We focus on critical life-cycle periods over which to construct individual-specific disaster exposure variables. The periods include the most recent year prior

11. While early life exposure age-in-months (e.g., 1st, 2nd, 3rd month after birth) windows would be homogeneous across children with the same birth dates in the same location, recent exposures of the same duration would match up to different age-in-months windows depending on the child age at the time of the survey. Hence, we include an individual-specific i subscript for FM_{ij} and LM_{ij}.

to the survey month (including the survey month), the year before the most recent year, the first 1,000 days (early life), and the time between early life and the two years prior to the survey month. It is feasible to construct child life-cycle disaster histories because interview years and months and birth years and months are available for all children in our MICS sample.[12] The oldest child in the sample was born in December 1999. We track EM-DAT disasters from 1999 to 2019 and match 355 disasters that happened in that period in our sample locations to children based on the calendar-month timing of disasters.

Disaster-Intensity Types. We define several disaster-intensity types: any disasters, only floods, severe disasters (defined as causing more than 500 deaths or injuries or affecting 5,000 people or more), and only severe floods. Out of a total of 355 disaster events, 155 were categorized as floods. Severe disasters accounted for 174 out of the 355 events. Within this subset, floods emerged as the most frequent event, with 93 incidents, which were subsequently classified as severe floods with characteristics shown in Table 3.

3 Summary Statistics

3.1 Sample Overview, Individual and Parental Characteristics

As stated above, our sample of children is from the MICS6 5-to-17 Child Questionnaire module. These data provide information on enrollment and foundational-math-learning-assessment-test scores for these children. However, the sample sizes differ for enrollment versus math-test scores because only children aged 7 to 14 years participated in the foundational-learning assessment (subject to their availability at home and parental consent during the survey). In Table 1, we show that the country-specific samples were collected between 2017 and 2019 and also show the geo-identifiers at the finest available administrative levels for each country survey.[13] For example, children from Bangladesh are identified based on which district (administrative level two) they live in, while children from the Kyrgyz Republic are identified based on which Oblast (administrative level one) they live in.

In Table 2, we show summary statistics for all children across all variables except for disaster exposures in two panels. The total sample includes 144,471 children, with 48% being female. We present the distribution of the sample by country and age in Figure C.1. The average enrollment rate in the current school year when the children were surveyed is 79%, and 90% of the children aged 7–14 have math-test scores. Note that this means that the sub-sample of children who took the tests would be much more selected if it were given in schools, and therefore limited to those enrolled and attending school, rather than given at home. We find larger shares of children co-residing with mothers than with fathers and more mothers who are alive than fathers, with Figure C.5 and Figure C.6 presenting these statistics by children's ages. We find that by age 17, about 9% of the children in the sample no longer have fathers who are alive and 25% of the sample are no longer living with their fathers. In contrast, the shares of

12. The interview calendar day is observed for sample children as well, but we only use year and month information to match disasters to child life-cycles because the birth calendar day is not observed for all children.

13. The definition of region differs across countries. It is district for Bangladesh, Oblast for the Kyrgyz Republic, district for Pakistan, and changwat for Thailand, respectively, and region for other countries.

children with mothers who are alive are above 96% across all ages, and the shares of children living with mothers are larger than 85% across all ages.

In Table C.2 and Figure C.4, we break down the sample by country and show information on mothers' schooling levels and whether children live with their parents. In Turkmenistan, the Kyrgyz Republic, Thailand, and Mongolia, the shares of mothers who have ever been enrolled in school are larger than 94%. In contrast, in Bangladesh and the three provinces of Pakistan, the shares are 74% and 36%, respectively.[14] In the Kyrgyz Republic, the shares of mothers with higher than secondary education and who have ever been enrolled in school are both higher than 90%, but in all other countries, the shares of mothers with secondary education account for 25% to 68% of the shares of mothers who have ever been enrolled in school.

3.2 Educational Outcomes

In Table 2, we show overall summary statistics for educational variables, including enrollment this year, enrollment last year, math-test scores, and attainment (grades completed) at the start of the school year. In Table C.1, we break down heterogeneities in these variables by country. In Thailand, only children up to 14 years old are surveyed; in other countries, averages are based on all children between ages 5 and 17. We find that among the countries we study, MICS6 children in Pakistan have the lowest enrollments, followed by Bangladesh.

Enrollment. In Figure 1, we present the enrollment status in the survey year. Compared to boys, current enrollment for girls is higher in Bangladesh, significantly lower in Pakistan, and similar in other countries. Enrollments in the current year, as well as in the preceding year, generally go up for children up to 10 years of age and then decline for older children in all countries. Across countries, we also find that the likelihood of current non-enrollment is significantly higher if a child was not enrolled in the previous year. Specifically, Figure C.7 shows that the proportion of children who were enrolled in the year prior to the survey and continued their enrollment in the survey year exceeds 95% up to age 14 but declines to 88% by age 17. The proportion of children who re-enroll after a year of non-enrollment diminishes with age, falling below 10% after age 11.

Educational Attainment. Educational attainment is defined as the highest grade completed by a child at the time of the survey. The results on attainment by age and country are shown in Figure 2. The average attainment for children (5–17 years old) varies by country, with Mongolian children having the highest average attainment and Pakistani children having the lowest average attainment. Compared to boys, the average attainment for girls is higher in Bangladesh, Nepal, and Thailand, significantly lower in Pakistan, and similar in other countries.

Test Scores. Average math-test results by age and country are shown in Table C.1 and Figure 3. Compared to other countries, average math scores are lower in Nepal and Bangladesh

14. According to a report on Pakistan from the Demographic and Health Surveys (DHS) Program (National Institute of Population Studies and ICF 2019), half of women aged 15 to 49 who have ever been married have no schooling. Half of children under 5 have mothers without schooling, and women without schooling have 1.6 more children than women with higher education.

and lowest in Pakistan. Test scores are similar for both genders, except in Pakistan, where male scores are significantly higher. Given the uniform test administered to children of all ages, as expected, older children perform better on average than younger children. As shown in Figure 3, children from Turkmenistan, the Kyrgyz Republic, and Thailand have relatively high average scores that rise gradually across age groups. Children from Nepal and Bangladesh have medium levels of the average performance, which increases steeply as children age. Children from Pakistan have the lowest math-test scores, and average scores have slow growth as age increases. In particular, the average math-test score in the Sindh province of Pakistan at age 14 is less than half of the average test score for children in Thailand at age 7.

3.3 Disaster Exposures

We present summary statistics of disasters linked to geographic locations in Table 3. Our analysis focuses on four categories of disaster exposure relevant to educational outcomes: any disaster recorded in EM-DAT, floods, severe disasters, and severe floods. In Asia and the Pacific, floods are the most common type of disaster (UN-ESCAP 2023). In the countries of interest, more than five flood events typically occur each year. Floods affect a large number of individuals annually. Even those in the first quartile of the distribution impact up to 3,100 people. Although floods generally have lower mortality rates compared to other disasters as shown in Table C.3, they exhibit substantial variation in severity and can affect wide geographic areas. Given their high frequency, widespread impact, and direct implications for health, exposure to floods during early childhood is likely to have long-term consequences for human capital formation (Maccini and Yang 2009).

With the linked MICS and EM-DAT disaster-exposure data, we present the shares of children in the MICS sample who were exposed to disasters in Table 4. We report exposure rates for four types of disaster events. 57% of children across the seven countries experienced disasters in the most recent 12 months, and 63% of children experienced disasters in the year prior to 12 months ago. Table C.4 highlights cross-country variation in exposure rates. Mongolia, Bangladesh, and Pakistan report the highest rates of recent exposures, with 86%, 73%, and 62% of children affected in the 12 months preceding the survey, respectively. In contrast, Nepal shows a lower share of recent exposure but a higher cumulative number of disaster months during early childhood. Figure 4 further illustrates the timing of disaster exposures, displaying the proportion of location-months affected by different disaster types across calendar months and countries. The results reveal a seasonal pattern, with disaster occurrences peaking during the summer months.

4 Estimation Strategy

Given variations across geo-identifiers and survey dates (see Table 1), we identify the effects of disaster exposures on school enrollments (E) and math-test performance (S) by comparing successive child cohorts within the same subnational locations. We jointly exploit temporal and spatial variation in disaster exposures by modeling educational outcomes as a function of natural-disaster exposures, with household and child characteristics as controls, along with time and location fixed effects. To explore effects heterogeneities moderated by child- and household-specific factors, we also estimate the model allowing for combinations of interactions between natural disasters and gender, age, and country.

Enrollment and Exposure History to Disaster Shocks. In models of children's schooling enrollment, households make binary schooling enrollment decisions given trade-offs between children going to school and the alternatives of children staying at home or working (Attanasio, Meghir, and Santiago 2012; Todd and Wolpin 2006; Casco 2022). Without enrollment, children cannot complete additional grades; with enrollment, children have some probability of passing the grade and thereby increasing their educational attainment (Attanasio, Meghir, and Santiago 2012). The gains from enrollment come from the expected value of increases in educational attainment and achievement by the start of the next school year; the costs of enrollment include the pecuniary and non-pecuniary, direct, and opportunity costs of going to school in the current period (Todd and Wolpin 2006).

In the current period, decision-makers might consider jointly as key state variables the existing levels of educational attainment (grades completed), prior enrollment decisions (potential difficulty with re-enrollment after dropout), and children's ages. These factors jointly determine the benefits and chances of school progression. Additionally, decision-makers also consider realized or expected shocks at the time of making enrollment decisions, and these can generate random variations in the relative gains and losses from enrollment. In this paper, we estimate a reduced-form model of enrollment decisions as a function of children's ages, prior attainments, prior enrollments, and disaster shocks.

For disaster shocks, first, we consider recent disaster shocks that match the timing of the enrollment decisions. Recent disaster shocks in location l at time t might increase both the direct cost (e.g., through increased costs of transportation) and indirect cost (e.g., through higher opportunity costs of helping out the household at home during disasters) of enrollment. These recent disaster shocks might also reduce the gains from enrollment by decreasing the chances of school progression and completion.

Second, we include early life disaster shocks to allow for differential critical-period disaster effects. Children could experience poorer health and educational outcomes in the long run if they are exposed to adverse prenatal and postnatal environments (Cunha et al. 2006; Almond, Currie, and Duque 2018; Pazos et al. 2024). Exposures to early life shocks have been found to have large effects on later-life health and nutrition conditions (Maccini and Yang 2009; Dimitrova and Muttarak 2020; Randell, Gray, and Grace 2020; Hirvonen, Sohnesen, and Bundervoet 2020; Skoufias and Vinha 2012; Thai and Falaris 2014; Rosales-Rueda 2018). While lagged attainment and enrollment variables can capture the indirect effects of earlier shocks on current enrollment, they do so only under the assumption of geometrically declining effects of impacts from all prior periods, and they do not allow for critical-period deviations (Todd and Wolpin 2003). However, early life disaster shocks might have formative impacts on the cognitive and non-cognitive skills, as well as the health status, of the child. Early-disaster-induced shifts in the underlying characteristics of children, which might not be fully captured by attainment and prior enrollments, could impact the expected net gains from enrollment, creating a direct channel for early life shocks to impact enrollment decisions differentially compared to shocks from more recent periods.

To analyze the relationships between enrollments and disaster experiences, we estimate the dynamic equation below with the lagged dependent variable for enrollments:

$$\begin{aligned} E_{ilt} =& \psi_0 + \psi_1 E_{il,t-1} + \psi_2 A_{ilt} \\ &+ \sum_{j \in \text{TimeSpan}} \beta_j^p D_{ilj}^p \\ &+ X_i' \theta + \mu_l + \mu_{g_i(t)} + \mu_t + \epsilon_{ilt} \ , \end{aligned} \tag{2}$$

where TimeSpan $= \{m12to1, first1000days\}$, with $m12to1$ representing the most recent year up to the survey month and $first1000days$ capturing the first 1,000 days from conception. $E_{il,t-1}$ is the enrollment status of child i living in location l in the last school year $t-1$. A_{ilt} is the grade completed at the start of period t. D_{ilj}^p denotes the natural disaster shock of type p experienced by child i in location l during time span j. We control for a vector X_i of observed individual and parental characteristics, including mothers' education, whether the child resides with their parents, and whether their parents are alive.

We control for sub-national location fixed effects μ_l, which are at the same level (or lower) of geographical aggregation as the disaster variables, child-age fixed effects $\mu_{g_i(t)}$, and survey-time fixed effects μ_t.[15] The distributions of household and location characteristics that impact the trade-offs from enrollment could systematically differ across locations with more or fewer disasters. Through location fixed effects, we control for these to the extent that this is possible by comparing children within location l given different experiences of disasters due to within-location survey-month heterogeneities and within-location child-age heterogeneities: the former strategy generates differences across children in recent exposures within locations, and the latter generates differences across children in life-cycle exposures to disasters within locations and survey months. Furthermore, our calendar-timing fixed effects pick up possible correlations between disasters and enrollments due to within-year seasonality patterns and secular trends.

Achievement and Exposure History of Disaster Shocks. We model educational achievement—MICS-administered math-test scores—as the output of a human-capital-production function (Todd and Wolpin 2003; Hanushek and Rivkin 2012). The inputs to the production function include all prior child, family, school, neighborhood, and environmental inputs. Inputs from a particular stage in a child's life might have heterogeneous effects on the child's achievement at different ages, and inputs from different stages of a child's life might have heterogeneous effects on the achievement at a particular age.

In many empirical settings, it is difficult to obtain the full history of inputs, so researchers often rely on strategies with short panel data and strong assumptions about the production technology (e.g., geometrically declining weights on past inputs) to estimate value-added production functions with limited input histories (Hanushek and Rivkin 2012). In our setting, we have a

15. We consider the survey interview timing by controlling for survey year $\times$ month fixed effects. For notational simplicity, we suppress the survey month subscript. $g_i(t)$ denotes the individual-specific age function that maps between the interview calendar month and child age g.

cross-section of child outcomes, complemented with child-specific histories of disaster exposures constructed using the EM-DAT disaster dataset. Our strategy is to estimate the effects of past disasters on achievement by including the full history of disasters, thereby assessing the heterogeneous effects of disasters at different stages of children's life-cycles. Unlike child, family, school, and community inputs, disasters are not endogenous choices made by parents or children. Nevertheless, children, families, schools, and communities can respond endogenously to disaster shocks by changing their inputs in children's human capital production functions. Here, we only consider the history of disasters and not other inputs. This means that our estimates for disasters will include the direct effects of disasters, as well as indirect effects due to endogenous changes driven by disasters in other unmodeled inputs.

Specifically, following the human-capital-production-function framework, we estimate the relationships between the life-cycle of EM-DAT disaster exposures and MICS-administered achievement tests using the following specification:

$$S_{ilm} = \alpha + \sum_{j \in TimeSpan} \beta_j^p D_{ilj}^p + X_i' \theta + \mu_{c(l),A_i(m)} + \mu_l + \mu_{g_i(m)} + \mu_m + \epsilon_{ilm} \ , \tag{3}$$

where S_{ilm} is the score on the MICS-administered test achieved by child i in location l in survey month m. We succinctly consider the child's life-cycle of disaster exposures in several life-cycle time segments, TimeSpan $= \{m1to12, m13to24, midchildlife, first1000days\}$, which contain disaster exposure in the most recent year, the second most recent year (year prior to the most recent year), the years between the second most recent year and first 1,000 days (a span that we describe as mid-child life), and the first 1,000 days. We compare test scores, controlling for location fixed effects μ_l, survey-timing fixed effects μ_m, child-age fixed effects $\mu_{g_i(m)}$, and country- and attainment-specific fixed effects $\mu_{c(l),A_i(m)}$.

When estimating Eq. (3) for children from all ages jointly, we implicitly assume that the differing effects of early, mid-life, and recent disasters on children are all homogeneous as the child ages. In Eq. (4), we relax this assumption and allow for current-age-specific disaster-history effects $\beta_{g_i(m),j}^p$:

$$S_{ilm} = \alpha + \sum_{j \in TimeSpan} \beta_{g_i(m),j}^p \cdot D_{ilj}^p + X_i' \theta + \mu_{c(l),A_i(m)} + \mu_l + \mu_{g_i(m)} + \mu_m + \epsilon_{ilm} \ , \tag{4}$$

where $\beta_{g_i(m),j}^p$ is exposure to a type-p disaster intensity in period j, which is specific to a child aged $g_i(m)$ in survey month m. Our estimation strategy exploits heterogeneities in disaster histories within locations and across individuals. In practice, because conditional on the location and age-in-months jointly, there are no variations in child exposure histories, we cannot estimate Eq. (4) with separate $\beta_{g_i(m),j}^p$ values for each age-in-months. We implement Eq. (4) by allowing for heterogeneous disaster effects for children across different age groups (7 to 9, 10 to 12, and 13 to 14 years), with the assumption that the effects of disaster histories are homogeneous within each age group.

5 Results

From our analysis based on the enrollment model, we find that after the lower primary grades, there are weak negative effects of recent disaster exposures on enrollments and persistent negative direct effects of early life disaster exposures on enrollments. We find generally larger negative impacts on enrollments for boys and greater enrollment impacts from exposure to floods, severe disasters, and severe floods compared to exposures to "all disasters."

From our child skills life-cycle production function analysis, we find no effects from recent disaster exposures, weak negative effects from mid-child life disaster exposures, and stronger negative effects of early life disaster exposures on math-test scores. Early life disasters have more persistent effects on girls and exposures to floods have generally larger negative effects than exposures to other types of disasters.[16]

5.1 Disaster Experiences and Enrollments

We estimate Eq. (2) using a linear probability model and present the results in Table 5. We consider the effects of both having experienced any disaster in the most recent 12 months and the number of months with disasters in the first 1,000 days on enrollments in the current school year. In column (1) of Table 5, we consider all disasters regardless of their category or severity. Averaging across children from ages 5 to 17, we find significant direct negative effects of early life disaster exposures on enrollments, and a weak negative relationship between recent disaster exposures and enrollments. Specifically, each additional month in the first 1,000 days exposed to EM-DAT disasters reduces enrollments by 0.1 percentage points. The overall 10th to 90th percentile range for the number of months exposed to early life disasters is 0 to 8 months, with an average of 3.0 months and a standard deviation of 3.7 months. A shift from the 10th to the 90th percentile of early life disaster exposure would, on average, lead to about a 1-percentage-point reduction in enrollments.

We find strong positive associations between current enrollments and lagged enrollments and attainment (see Appendix Table C.6). We also find generally consistent patterns of relationships between child, parental, and household characteristics and enrollments from Table 5. Specifically, we find that girls have lower enrollments than boys by 0.6 percentage points, having a mother who has ever been educated is associated with higher enrollments by 4.1 percentage points, and having a mother with secondary schooling is associated with higher enrollments by an additional 1.1 percentage points. Interestingly, we find that having a mother who is living in the same household is associated with an increase in child enrollments by 2.5 percentage points. In contrast, while having a father who is alive increases enrollments by 1.2 percentage points, having a father living in the same household is associated with a reduction in enrollments by 0.5 percentage points.

16. For the main results in the text, we do not apply the MICS6 probability weights because weights for 3,683 observations in our sample are zero with no documentation as to why, there are questions about how best to weight across countries, and the use of weights does not always improve causal estimators and can reduce efficiency and their application is not always warranted (Solon, Haider, and Wooldridge 2015). We discuss the use of the MICS6 weights and how we apply them to alternative estimates in Appendix A.4.

5.2 Disaster Experiences and Math Skills

In Table 6, following Eq. (3), we present results from estimating the effects of child-specific life-cycle disaster histories on math-test scores, which are available for children 7 to 14. Parallel to the presentation of the enrollment results, Table 6 presents results in four columns by disaster-intensity type, and it includes various fixed-effects and individual-specific controls. Coefficient estimates are on the scale of the MICS math-test scores (see Figure 3), which vary between 0 and 21 points. Averaging across children 7 to 14, Table 6 shows no effects of recent disaster exposures, weak negative effects of mid-child life disaster exposures, and significant negative effects of early life disaster exposures on math scores. In particular, an additional month of mid-child life and early life disaster exposures reduces test scores by 0.024 and 0.031 points, respectively. Given the standard deviations for math-test scores across countries (see Table C.1), a shift from the 10th to the 90th percentile of early life disaster exposures would lead to average test score reductions of 0.09 and 0.04 standard deviations in the Kyrgyz Republic and Nepal, which have the second-lowest and second-highest math-test score standard deviations in our sample.

Additionally, we find consistent patterns of relationships between child, parental, and household characteristics and math-test scores across the columns of Table 6. Girls are found to have lower scores than boys, holding other factors constant. Having a mother who has ever been educated is associated with higher scores, and having a mother with secondary schooling is associated with even higher math scores. Additionally, having a mother who is alive is positively associated with test scores. Having a father who is alive is also associated with higher test scores, but the effects disappear if the father does not reside with the child.

5.3 Effects from Different Types of Disasters

In columns (2) to (4) of Table 5, we move beyond average effects across all disasters and compare children with and without exposure to floods, severe disasters, and severe floods (see Section 2.2). In column (2) of Table 5, compared to children who did not experience floods, we find that children with recent flood exposures have a lower rate of current enrollments by 1.2 percentage points. However, the recent-exposure effects are insignificant for severe-disaster and severe-flood exposures. For early life disaster exposures, we find that the estimated effects of flood (column 2) and severe-disaster (column 3) exposures are double the negative "all disasters" estimates from column (1), and the effects of severe-flood (column 4) exposures quadruple the column (1) results. The results from columns (2) to (4) can be viewed as lower bounds on type- and severity-specific disaster exposures, because we pool all children who did not experience floods, severe disasters, and severe floods into respective comparison groups, including children who experienced other types and less severe types of disasters.

The estimated average effects of disaster exposures on math skills by disaster type are shown in columns (2) to (4) of Table 6. We find that while floods in recent years have no significant impacts and floods during mid-child life have only weak negative effects on math-test scores, the negative effects of early life flood exposures are twice as severe as the negative effects of early life exposures to "all disasters." We also find imprecisely estimated negative effects of severe-flood exposures but find close-to-zero effects for severe-disaster exposures on math-test scores. As discussed previously, the estimates in columns (2) to (4) can be considered as lower bounds on the total effects of exposure to each type and severity of disaster—they are based on comparing children with a particular type and severity of disaster exposure history to all other children, including those who experienced different or less-severe types of disasters.

Overall, we find that exposures to floods have more pronounced negative effects on children's education than exposures to "all disasters". Compared to other disaster types, such as droughts or epidemics, floods often cause widespread disruption to transportation networks, destroy school infrastructure, and displace households. These disruptions tend to be more prolonged and geographically extensive, making regular school attendance more difficult. Moreover, floods frequently lead to outbreaks of waterborne diseases and sanitation crises, increasing illness among children and further hindering school participation, particularly in areas with limited healthcare access (Cadag et al. 2017; Huang and Dong 2025).

5.4 Heterogeneous Effects on Enrollments

We continue to estimate Eq. (2) using linear probability models, but we explore heterogeneity by child-age groups in Table C.9 and heterogeneity by joint child age and gender groups in Table 7. Age groupings are defined based on the primary education age-range across different countries. The 5-to-8 years age group corresponds to initial enrollment and lower-primary grades, the 9-to-12 years age group corresponds to upper-primary grades, and the 13-to-17 years age group corresponds to post-primary secondary-school grades.[17]

Results in Tables C.9 and 7, compared to the overall weak negative results for all children in Table 5, reveal stronger negative impacts of recent disaster exposure on school enrollment among children aged 9 to 17, particularly for boys. Early-life exposure to floods and severe disasters reduces enrollment by up to 0.4 percentage points for boys and 0.3 percentage points for girls within this age group. Notably, each additional month of early-life disaster exposure reduces enrollment by 0.3 percentage points among older children—approximately three times the average effect observed across all children. In columns (2) to (4) of Table 7, we also find consistent negative enrollment effects of exposure to recent floods and severe floods for boys 9 to 17. For younger children (ages 5–8), we find that early disaster exposure negatively affects enrollment for girls but not for boys—suggesting an early disadvantage for girls at the start of primary school. Unexpectedly, recent-severe-flood exposures lead to increase in enrollments, particularly among younger children. This suggests that in the aftermath of severe disasters, younger children may be more likely to be enrolled in school. We explore potential explanations for this counterintuitive finding in later sections.

About 80% of the sample comes from Bangladesh and Pakistan, so the estimates potentially pertain largely to these two countries. We explore heterogeneity by joint country and age groups regarding all disasters for Pakistan, Bangladesh, and other countries in Table 8. The results broadly align with our main findings. In Pakistan, we observe negative effects of both

17. In Bangladesh, Mongolia, Nepal, and Pakistan, the official primary-school entrance age is 6 years and the primary-school cycle spans 5 years. In the Kyrgyz Republic, the official primary-school-entrance age is 7 years, with the primary-school cycle lasting for 4 years. In Thailand, primary school officially encompasses children 6 to 12 years old. In Turkmenistan, the official primary-school-entrance age is 6 years and the primary-school cycle lasts for 4 years.

recent and early life disaster exposure on enrollment across all age groups, with the strongest effects for children aged 5–8. In Bangladesh, both recent and early exposures show an increasing negative impact with age, suggesting that older children's enrollments are more vulnerable to disruptions.

5.5 Heterogeneous Effects on Math Scores

We estimate the heterogeneous effects of life-cycle disaster exposures on math scores by age groups in Table C.10 and by joint age and gender groups in Table 9. Although the effects of disaster exposures in recent life, mid-child life, and early life are all estimated, we only present those for mid-child and early life because the effects of recent-disaster exposures remain insignificant in all regression results. Given that math scores are only available for children 7 to 14, we divide these children into three age groups: the 7-to-9 age group corresponds to lower-primary grades, the 10-to-12 age group corresponds to upper-primary grades, and the 13-to-14 age group corresponds to initial post-primary grades.

We continue to find weak negative effects of all disaster exposures in mid-child life on math scores across all age groups. We find generally larger magnitudes of negative effects for mid-child life flood and severe-disaster exposures on math scores for children 10 to 14, with flood-effect magnitudes being approximately double the magnitudes of the "all disasters" effects. We find that early life disasters' negative effects on math-test scores for lower-primary and post-primary children are similar in magnitudes compared to the average effects from Table 6. For lower-primary and post-primary children, we also find that early life exposures to floods, severe disasters, and severe floods have weakly negative math-test effects that are similar or larger in magnitude compared to the "all disasters" effects. Breaking down the results by gender in Table 9, across disaster types, we find consistently negative but generally imprecisely estimated early life disaster exposure effects for lower-primary and post-primary children. For girls and boys, an additional month of early life disaster exposures leads to point reductions of 0.041 and 0.036 in early primary math-test scores and point reductions of 0.041 and 0.018 in post-primary math-test scores; the post-primary estimates for girls and boys, respectively, are about 30% larger and 40% smaller than the average effects from Table 6. Our results indicate that early disaster impacts are comparable for boys and girls at the beginning of primary school, but boys exhibit a greater catch-up with age, which helps to mitigate the initial negative effects. Our findings relate to the literature that has shown the importance of critical periods. Children in their critical first 1,000 days at the time of disasters have been negatively affected on the height-for-age health indicator, with the youngest being the most affected (Andrabi, Daniels, and Das 2021). A low height-for-age value may indicate stunted physical growth affecting also cognitive ability. There is evidence of strong correlations between height and test scores in both developing and developed countries. (Case and Paxson 2010; Glewwe, Jacoby, and King 2001; Glewwe and King 2001; Hoddinott et al. 2013).

In Table 10, we estimate heterogeneous effects by country and age groups for all disasters. Similar to the overall findings, we find consistent negative mid-child life disaster-exposure effects on math-test scores in Pakistan and Bangladesh across age sub-groups. The results for other countries are generally imprecisely estimated. Due to differences in age composition and disaster histories across countries, there is limited within-country variation in exposure during early and middle childhood. This lack of variation makes it difficult to precisely identify country-, life-cycle-, and age-specific effects of disaster exposure, whether considering all disasters or only severe ones.

5.6 Potential Mechanisms and Explanations

Gender-and-age-differentiated educational decisions. Gender and age both play important roles in shaping educational decisions in many developing country contexts. Existing studies highlight that school dropout often serves as a form of household self-insurance in response to negative economic or environmental shocks. This coping mechanism tends to vary not only by gender but also by the child's age, with older children more likely to leave school to support household needs. Our findings align with this literature by underscoring how disaster exposure differentially affects school enrollment across both gender and age groups. For example, a study in Mali found that exposure to locust plagues reduced enrollment in boys, while girls' educational attainment suffered more in terms of grade progression (De Vreyer, Guilbert, and Mesple-Somps 2015). In some regions of Pakistan, males are prioritized in educational investments in households, contributing to gender gaps (Raza, Shah, and Haq 2022). On the other hand, given that disaster exposure can generate both short- and long-term income shocks, it is plausible that older boys may be more likely to drop out of school to help support the household, while younger children or girls may face fewer such trade-offs. Illustrating the point with evidence from a region of Fiji struck by a cyclone, Takasaki (2017) argues that declines in girls' disadvantage in schooling in some developing countries "can be partly explained by a gendered division of child farm labor as a coping response to natural disasters". When men are more active in farming than women, they argue that child farm laborers are mostly boys, such that when disaster strikes, coping via "school dropout and child labor as self-insurance" tends to disadvantage boys' education. In Guatemala, early life nutritional interventions improved schooling outcomes for girls but not for boys, as the opportunity cost of work increased for boys with better nutritional status (Maluccio et al. 2009). Wu, Lin, and Han (2023) show that positive rainfall shocks in birth years improve long-term test scores and schooling for girls, but not for boys. Hence, gender differences in schooling outcomes, affected by natural disasters, could be explained by the insurance role of boys and girls as such a short-term coping mechanism (i.e., gendered division of child labor).

Localized policies and recent disaster effects. In addition to early life exposures, recently occurring disasters can disrupt schooling, reduce household income, and increase disease risk—all of which may lead to reduced enrollment and other educational outcomes. Our findings suggest that the effects of recent disaster exposure on school enrollment are heterogeneous and vary by gender, age, and country context. In some cases, school enrollment increases following disaster events—a pattern that may seem counterintuitive at first. Several plausible explanations may account for this finding. First, schools can serve as protective environments in the aftermath of disasters, offering children a sense of stability, routine, and hope. This structure may be particularly valuable for families coping with crises, as schools also provide supervision and safe spaces, encouraging parents to maintain or increase their children's enrollment (INEE 2024). Second, schools often function as central sites for relief distribution, providing access to food, clean water, medical care, and psychosocial support. Parents may choose to enroll their children to ensure they benefit from these essential services. Disaster exposure may heighten parental risk aversion and increase perceived vulnerability, leading some families—particularly those in flood-prone areas—to prioritize education over riskier livelihoods such as agriculture (Botzen, Aerts, and Bergh 2009). Third, governments and NGOs frequently implement disaster-response programs to promote educational continuity. In Pakistan and Thailand, for example, efforts have been made to keep schools functional post-disaster—such as draining floodwater promptly and promoting safe learning environments (Siddiqui, Towheedul Islam, and Akhter 2015; Syverson 2024; National Disaster Management Authority (Pakistan) 2017; Jansuttipan 2022). Fourth, while older children may drop out of school to work in response to household income shocks, younger children (ages 5–8) are typically too young to enter the labor force. In some contexts, macroeconomic disruption from disasters may also reduce short-term labor opportunities, thus encouraging continued school attendance (Kousky 2016; Behrman, Deolalikar, and Tinakorn 2001). This may help explain why we observe increases in enrollment in some settings, though most studies in low- and middle-income countries tend to find that disasters lead to reduced schooling (Gitter and Barham 2007; Baez and Santos 2007).

5.7 Robustness

This section presents robustness analysis of our main results. To assess the robustness of our estimates to alternative disaster-exposure measures and model specifications, we conduct a series of empirical tests. In Table C.6, we show the effects of "all disasters" on school enrollment using an alternative specification with fewer control variables. Across columns, we consistently find strong positive associations between current enrollment and both lagged enrollment and educational attainment, regardless of whether individual and parental characteristics are included. Adding or removing country- or age-specific trends in prior enrollment and attainment does not alter the direction or significance of the estimated effects of disaster exposure on enrollment. Table C.7 explores the sensitivity of enrollment outcomes to alternative definitions of disaster exposure. We test different measures, including binary indicators for exposure during the survey month, exposure within the most recent three months, and a continuous variable counting the number of months with disaster exposures. The results remain consistent across specifications. Table C.8 presents analogous robustness checks for math-test scores. Columns (2) and (3) incorporate more granular disaster-exposure measures, refining the temporal scale from annual to monthly. These results further reinforce the credibility of our main findings.

We also address concerns about potential selective migration in response to disasters by analyzing a subsample of children whose mothers are observed to have resided in the same city, town, or village for longer than their children's ages—thus likely capturing only non-migrant households. In our main sample, which includes all children in MICS6, approximately 32% cannot be matched to a mother. Among the matched cases, 88% of children have mothers whose duration of residence exceeds their children's ages, resulting in a restricted subsample of about 86,700 children. As discussed in Section 2.3.3, this analysis likely over-corrects for potential migration because most of the sample exclusion are due to maternal data not being collected in certain survey regions, and observed movers may have relocated within the same disaster-linked MICS administrative unit. We estimate the effect of disaster exposure on enrollment and math scores for the stable-residence subsample. Results are shown in Table C.11 (compared to Tables 5 and C.6) and Table C.12 (compared to Table 6). For this subsample, the effects of early-life exposure to all disasters on enrollment are weaker and no longer statistically significant, whereas the effects of floods and severe disasters remain negative. Regarding math performance, although the magnitudes of the estimated effects change, we still observe persistent negative impacts of early-life disaster exposure. If mothers had migrated to less-affected areas in response to disasters, estimates from the full sample could underestimate the true effects, as some "treated" children may be misclassified as "controls". The consistency of results in the restricted sample supports the robustness of our findings, suggesting that early life disaster exposure negatively affects enrollment and academic performance, even when accounting for potential migration bias.

6 Conclusions

Climatic-change-induced disasters pose particularly serious threats in Asia and the Pacific, which is the world's most natural-disaster-prone region (UN-ESCAP 2023). It accounted for nearly one third of weather, climatic, and water-related disasters globally, nearly half of all deaths, and one third of the associated economic losses between 1970 and 2019 (United Nations 2021). As disaster resilience is becoming a more important policy concern, particular attention is being given to its impact on children, who are especially vulnerable.

In this paper, we estimate the impacts of natural disasters on children's educational outcomes, including school enrollments and human-capital accumulation as measured by math skills, using data from seven Asian and Pacific region countries. We construct novel panels of child-specific disaster-exposure histories, with an emphasis on exposures in the first 1,000 days from conception, middle childhood, and the period immediately preceding the surveys and tests. We allow the impacts of disasters to differ depending on the ages at which children were exposed, as well as their current ages at the time of enrollment or test-score measurements. Given correlations in disaster exposures across time and within locations, the joint consideration of children's disaster exposures over their lifetimes allows estimates of the associations with earlier and later disaster exposures to not be contaminated by each other. Additionally, our novel dataset brings together a large international sample that allows the use of fine location and time fixed effects to control for time-varying and location-specific unobserved heterogeneities that might be correlated with disaster histories and human-capital outcomes.

Our results show significant negative effects of early-life disaster exposure on school enrollment and math skills, while recent exposures have weaker or no effects. Both boys and girls are affected adversely, though in different ways: boys are vulnerable in terms of school enrollments to having experienced natural disasters in early life, while girls' performances on MICS-administered math tests are harder hit by early life natural-disaster exposures. Floods—particularly severe floods—are more detrimental than other disaster types. Heterogeneity analysis shows that early life exposure to disasters, especially floods, reduces enrollment, with girls aged 5–8 particularly affected. Recent severe floods, however, are associated with increased enrollment among young children of both genders, particularly among children aged 5–8, but not among older cohorts. These findings may reflect shifts in parental risk aversion, family decision-making, and the role of schools as support centers in the aftermath of severe floods. For math scores, the effects of early life exposure for lower-primary and post-primary children are roughly similar in magnitude to those for all children considered. Mid-child life exposure effects are rather weak and similar for all age groups considered. The early life exposure impacts are also comparable for boys and girls at the beginning of primary schools, but boys exhibit greater catch up on test scores with age mitigating the initial negative effects.

Our study contributes to the existing literature in several ways. First, as we study not only short-term disaster shocks but also early life shocks, and contribute to a large body of literature addressing the immediate and lasting effects of disaster shocks on children's human-capital outcomes. Second, we explore regional and local heterogeneities, as well as variations by age and gender, and consider child life-cycle exposures to multiple disasters across disaster types. By using a substantial sample that includes over 140,000 children from seven Asian countries and a global record of natural disasters, we are able to provide a broader perspective than studies limited to single countries. Rather than limiting our exploration to one type of disaster in one country, as in much of the previous literature, we consider a range of natural disasters in seven countries. We find, nevertheless, that one type of disaster, namely floods, tends to have the largest effects on educational outcomes in the countries of interest. The findings underscore the necessity of targeted interventions to support children affected by disasters, particularly floods, during their formative years.

Our study has limitations. First, our construction of disaster-exposure histories relies on the assumption that children have continuously resided in the same location throughout their lives and until the survey year. For a subsample, we observe that mothers have remained in the same location for periods longer than their children's ages, but we are unable to capture cases where children may have temporarily migrated and later returned. This limitation highlights the potential value of more detailed migration histories for both children and parents, or ideally, a panel data structure. Second, despite EM-DAT's considerable value as a resource for cross-national and cross-disaster research that provides broad coverage across countries and disaster types, the accuracy of disaster exposure measures could be improved with more granular information, particularly on localized events in less-studied countries. Additionally, since EM-DAT's inclusion criteria are based on human loss rather than broader metrics such as crop damage or infrastructure loss, the dataset may not capture the full range of disaster impacts. This limitation constrains our ability to identify specific mechanisms, such as whether individuals were physically harmed or experienced food insecurity due to agricultural disruptions. Further, EM-DAT records affected locations at administrative levels 1 and 2, but future research would benefit from finer geographic detail. Third, in the MICS6 data, some countries report only administrative level 1 identifiers, limiting our ability to match disaster exposure precisely. Future studies would benefit from more detailed geographic identifiers in the survey data. Fourth, the absence of detailed labor market and nutritional data in MICS6 restricts our capacity to investigate the impact pathways further. Fifth, regarding country-specific analyses, differences in sample composition and disaster histories across countries limit the within-country variation necessary for robust estimation.

Despite these limitations, this study makes an original contribution to the comparative study of disaster impacts on children. By pooling data across countries and exploring heterogeneities in disaster effects, our study offers comparative insights into how disasters influence educational outcomes in understudied contexts. Future research should further investigate disaster impacts in countries such as the Kyrgyz Republic, Mongolia, and Nepal, where evidence remains limited. Future data collection efforts in this line of research would benefit from longitudinal designs or additional attention to location histories of children, and from efforts to collect information on multiple pathways of disaster impact.

Tables and Figures

Table 1: MICS6 overview and key statistics for children 5 to 17 years of age

	Survey timeframe			Birth yr./mo.		Geo info		Obs
	Year	Start date	End date	Earliest	Latest	Geo-identifier‡	N	
South Asia								
Bangladesh	2019	01/19	06/01	2001/01	2014/05	District	64	40,617
Nepal	2019	05/04	11/13	2001/05	2014/10	Region	7	7,824
Pakistan	2017-19	2017 12/03	2019 10/23	1999/12	2014/10	District	97	71,121
East and Southeast Asia								
Mongolia	2018	09/17	12/24	2000/09	2013/12	Region	5	7,628
Thailand	2019	05/18	12/03	2004/06	2014/11	Changwat	18	9,608
Central Asia								
Kyrgyz Republic	2018	09/06	11/19	2000/10	2013/10	Oblast	9	3,897
Turkmenistan	2019	05/02	08/02	2001/05	2014/07	Region	6	3,776

Note: We focus on MICS6 countries with data collected prior to the onset of COVID-19. All data have national coverage except for Pakistan, where Balochistan is excluded due to survey overlap with COVID-19. ‡ Smallest geo-identifiers differ across countries. For example, 64 and 97 districts are included for Bangladesh and Pakistan, respectively.

Table 2: Summary statistics for all children

	Mean	SD	Min	Max	N
Panel A: Enrollment, math-test scores, attainment					
Ever enrolled (dummy)	0.88	0.33	0	1	144,426
Enrollment in last school year t-1 (dummy)	0.74	0.44	0	1	144,394
Enrollment in this school year t (dummy)	0.79	0.41	0	1	144,410
Have math score (dummy)	0.90	0.30	0	1	87,797
Math score (total)	14.09	7.37	0	21	78,704
Attainment (highest)	3.29	3.34	0	16	144,358
Attainment at start of last school year t-1	2.69	3.06	0	16	144,360
Attainment at start of this school year t	3.25	3.32	0	16	144,358
Panel B: Child and parental characteristics					
Age of child	10.49	3.78	4	17	144,471
Female (dummy)	0.48	0.50	0	1	144,471
Mother ever educated (dummy)	0.58	0.49	0	1	144,338
Mother has secondary-school education (dummy)	0.31	0.46	0	1	144,338
Mother is living in same household (dummy)	0.92	0.28	0	1	144,222
Father is living in same household (dummy)	0.81	0.39	0	1	144,068

Note: This table shows summary statistics of the combined-country sample on key educational variables in the first panel, child attributes and parental characteristics in the second panel. “Ever enrolled”, “Enrollment in last school year t-1”, and “Enrollment in this school year t” are dummy variables constructed from survey questions “Has (name) ever attended school or any Early Childhood Education programme?”, “At any time during the previous school year did (name) attend school or any Early Childhood Education programme?”, and “At any time during the current school year did (name) attend school or any Early Childhood Education programme?”, respectively. MICS6 also asks “which level and grade or year is (name) attending?” during “the previous school year” and “this current school year”, as well as “Did (name) ever complete that (grade/year)?”. To have uniform cross-country comparable attainment measures, we calculate the years of education completed from the above information as “Attainment at start of last school year t-1” and “Attainment at start of current school year t”. Using the survey question “What is the highest level and grade or year of school (name) has ever attended?”, we construct the variable “Attainment (highest)” with the same logic.

Table 3: Natural-disaster characteristics

Disasters	# of Events	Mean	SD	Min	1st quartile	2nd quartile	3st quartile	Max
All disasters	**355**							
Casualties	119	3,436	19,866	11	62	166	447	201,647
Affected	289	825,256	2,987,620	3	1,465	15,254	251,506	36,000,000
Flood	**155**							
Casualties	44	920	3,174	11	55	190	479	20,671
Affected	134	1,308,461	4,045,562	3	3,133	75,000	612,978	36,000,000
Severe disasters	**174**							
Casualties	67	6,006	26,272	11	89	347	1,043	201,647
Affected	174	1,369,814	3,756,295	1,500	27,281	146,388	831,880	36,000,000
Severe floods	**93**							
Casualties	26	1,465	4,070	11	61	352	867	20,671
Affected	93	1,884,549	4,750,148	5,067	65,000	385,498	1,497,725	36,000,000

Note: This table shows characteristics of the natural-disaster events linked to within-country locations from 1999 to 2019 to construct disaster-exposure measures. There are in total 355 disasters. Variable "Casualties" refers to the sum of number of total deaths and injured (if information on both is recorded for one disaster), and variable "Affected" refers to the total number of people affected. We present the distribution of human impacts for the four types of disaster shocks: any disaster recorded in EM-DAT, floods only, severe disasters only, and severe floods only.

Table 4: Summary statistics of disaster exposures for all children

	Mean	SD	Min	Max
Panel A: Any disasters				
Had disaster				
in most recent 12 mo.	0.57	0.50	0	1
in year prior to 12 mo. ago	0.63	0.48	0	1
# of mo. with disaster				
in mid-child life	7.75	9.04	0	60
in the first 1,000 days (early life)	3.05	3.73	0	24
Panel B: Floods				
Had disaster				
in most recent 12 mo.	0.33	0.47	0	1
in year prior to 12 mo. ago	0.49	0.50	0	1
# of mo. with disaster				
in mid-child life	3.39	4.45	0	23
in the first 1,000 days (early life)	1.35	2.11	0	11
Panel C: Severe disasters				
Had disaster				
in most recent 12 mo.	0.27	0.45	0	1
in year prior to 12 mo. ago	0.32	0.47	0	1
# of mo. with disaster				
in mid-child life	4.01	4.51	0	33
in the first 1,000 days (early life)	1.51	2.40	0	24
Panel D: Severe floods				
Had disaster				
in most recent 12 mo.	0.23	0.42	0	1
in year prior to 12 mo. ago	0.18	0.38	0	1
# of mo. with disaster				
in mid-child life	2.15	2.83	0	20
in the first 1,000 days (early life)	0.86	1.69	0	11

Note: This table shows summary statistics for child-and-location-specific disaster-experience indicators for various types of disasters. *Had any disaster* is denoted as DB^p in the equations—an indicator equal to one if there is a disaster of type p in the designated time span, and zero otherwise. *# of mo. with disaster* is denoted as DM^p, indicating the number of months with disasters of type p in the designated time span. The number of observations for all variables is 144,471. The mid-child life is defined as the period between the first 1,000 days and two years prior to the survey month.

Table 5: Effects of disasters on enrollments

	(1) All disasters	(2) Floods	(3) Severe disasters	(4) Severe floods
Had disaster in most recent 12 mo.	-0.004	-0.012^{**}	0.003	0.002
	(0.006)	(0.005)	(0.008)	(0.006)
# of mo. with disaster first 1,000 days	-0.001^{**}	-0.002^{***}	-0.002^{***}	-0.004^{***}
	(0.000)	(0.001)	(0.001)	(0.001)
Female	-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Mother is alive	-0.009	-0.009	-0.009	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)
Father is alive	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
Mother is alive × living in same HH	0.025^{***}	0.025^{***}	0.025^{***}	0.025^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
Father is alive × living in same HH	-0.005^{**}	-0.005^{**}	-0.005^{**}	-0.005^{**}
	(0.002)	(0.002)	(0.002)	(0.002)
Mother ever educated	0.041^{***}	0.041^{***}	0.041^{***}	0.041^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
Mother ever educated × secondary educ.	0.011^{***}	0.011^{***}	0.011^{***}	0.011^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	143,645	143,645	143,645	143,645
Within-country location FE	Y	Y	Y	Y
Interview year FE	Y	Y	Y	Y
Interview month FE	Y	Y	Y	Y
Child age FE	Y	Y	Y	Y
Enrollment $t-1$ × age group FE	Y	Y	Y	Y
Attainment t × age group FE	Y	Y	Y	Y
Enrollment $t-1$ × country FE	Y	Y	Y	Y
Attainment t × country FE	Y	Y	Y	Y

Note: This table shows regression results corresponding to Eq. (2). The first 1,000 days is defined as the period from conception to 24 months of age in child development; hence, in total, there are 33 months in the period. The average number of months with a disaster in the first 1,000 days is about 3 months. About 57% of children in the whole sample have experienced a natural disaster in the most recent 12 months. For the disaster intensity type, we consider all disasters, only floods, severe disasters (defined as causing more than 500 casualties or affecting at least 5,000 people), and only severe floods. Having various disaster intensity types provides the possibility for robustness checks on disaster experience construction. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table 6: Effects of disasters on math scores

	(1) All disasters	(2) Floods	(3) Severe disasters	(4) Severe floods
***Recent** experience: had disaster*				
in most recent 12 mo.	−0.070	−0.364	−0.015	−0.380
	(0.171)	(0.275)	(0.209)	(0.314)
in yr. prior 12 mo. ago	−0.014	0.016	0.213	−0.058
	(0.165)	(0.254)	(0.204)	(0.188)
***Mid-child life** experience: # of mo. with disaster*				
Between early life & recent yr.	−0.024	−0.022	−0.009	0.013
	(0.016)	(0.027)	(0.022)	(0.036)
***Early-life** experience: # of mo. with disaster*				
in the first 1,000 days	-0.031^{**}	-0.065^{***}	−0.008	−0.047
	(0.015)	(0.024)	(0.022)	(0.033)
Female	-0.420^{***}	-0.417^{***}	-0.419^{***}	-0.418^{***}
	(0.061)	(0.061)	(0.061)	(0.061)
Mother is alive	0.324^{**}	0.321^{**}	0.324^{**}	0.323^{**}
	(0.160)	(0.160)	(0.160)	(0.160)
Father is alive	0.227^{**}	0.226^{**}	0.225^{**}	0.226^{**}
	(0.105)	(0.105)	(0.105)	(0.105)
Mother is alive × living in same HH	0.057	0.057	0.056	0.056
	(0.080)	(0.080)	(0.080)	(0.080)
Father is alive × living in same HH	-0.217^{***}	-0.217^{***}	-0.216^{***}	-0.216^{***}
	(0.061)	(0.061)	(0.061)	(0.061)
Mother ever educated	1.340^{***}	1.337^{***}	1.343^{***}	1.341^{***}
	(0.082)	(0.082)	(0.082)	(0.082)
Mother ever educated × secondary education	0.996^{***}	1.000^{***}	0.997^{***}	0.998^{***}
	(0.067)	(0.067)	(0.067)	(0.067)
Observations	78,305	78,305	78,305	78,305
Within-country location FE	Y	Y	Y	Y
Interview year FE	Y	Y	Y	Y
Interview month FE	Y	Y	Y	Y
Child age FE	Y	Y	Y	Y
Attainment t × country FE	Y	Y	Y	Y

Note: This table shows regression results of math-test scores and disaster shocks. This corresponds to Eq. (3). The math-test score outcome is the absolute test score of each child. The first 1,000 days is defined as the period from conception to 24 months of age in child development; hence, in total, there are 33 months in the period. The mid-child life is defined as the period between the first 1,000 days and two years prior to the survey month. The length of mid-child life varies among individuals, with the average for all children being 84 months (S.D. is 46). About 57% of children in the whole sample have experienced a natural disaster in the most recent 12 months. The average number of months with a disaster in the first 1,000 days is about 3 months. The average number of months with a disaster in mid-child life is about 7.8 months. The average math-test score for all children in the sample is 14.20, with a standard deviation of 7.42. The distribution of math-test scores across ages and countries is shown in Figure 3. For the disaster intensity type, we consider all disasters, only floods, severe disasters (defined as causing more than 500 casualties or affecting at least 5,000 people), and only severe floods. Having various disaster intensity types provides the possibility for robustness checks on disaster experience construction. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table 7: Disasters and enrollments, heterogeneities across gender and age groups

	(1) All disasters	(2) Floods	(3) Severe disasters	(4) Severe floods
Had disaster in most recent 12 mo.				
× Male				
× Age 5–8	0.013	−0.019**	0.015	0.036***
	(0.009)	(0.009)	(0.011)	(0.009)
× Age 9–12	−0.010	−0.022***	−0.014	−0.031***
	(0.007)	(0.007)	(0.009)	(0.007)
× Age 13–17	−0.017	−0.011	−0.016	−0.036***
	(0.010)	(0.009)	(0.010)	(0.008)
× Female				
× Age 5–8	0.003	−0.019*	0.022*	0.053***
	(0.010)	(0.010)	(0.012)	(0.008)
× Age 9–12	−0.009	−0.005	0.007	−0.001
	(0.006)	(0.007)	(0.009)	(0.006)
× Age 13–17	−0.008	0.005	0.003	−0.011
	(0.009)	(0.009)	(0.010)	(0.008)
# of mo. with disaster in the first 1,000 days				
× Male				
× Age 5–8	0.001	0.002	0.001	−0.001
	(0.001)	(0.003)	(0.002)	(0.003)
× Age 9–12	−0.003***	−0.003***	−0.003***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
× Age 13–17	−0.001	−0.002**	−0.004***	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
× Female				
× Age 5–8	0.001	−0.005*	−0.002	−0.009***
	(0.001)	(0.003)	(0.002)	(0.003)
× Age 9–12	−0.000	−0.003***	−0.000	−0.002*
	(0.000)	(0.001)	(0.001)	(0.001)
× Age 13–17	−0.001	−0.002**	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	143,645	143,645	143,645	143,645
Within-country location FE	Y	Y	Y	Y
Interview year FE	Y	Y	Y	Y
Interview month FE	Y	Y	Y	Y
Child age FE	Y	Y	Y	Y
Enrollment $t-1$ × age group FE	Y	Y	Y	Y
Attainment t × age group FE	Y	Y	Y	Y
Enrollment $t-1$ × country FE	Y	Y	Y	Y
Attainment t × country FE	Y	Y	Y	Y

Note: This table shows heterogeneity analysis across countries and ages for disaster effects on enrollments. This corresponds to Eq. (2), with interacting disaster shocks between age groups and gender. The first 1,000 days is defined as the period from conception to 24 months of age in child development; hence, in total, there are 33 months in the period. For boys or girls in each age group (5–8, 9–12, and 13–17), about 56% of them have experienced a natural disaster in the most recent 12 months. The average number of months with a disaster in the first 1,000 days for children aged 5–8, 9–12, and 13–17 is about 2 months, 3 months, and 4 months, respectively. This does not vary across genders. For the disaster intensity type, we consider all disasters, only floods, severe disasters (defined as causing more than 500 casualties or affecting at least 5,000 people), and only severe floods. Having various disaster intensity types provides the possibility for robustness checks on disaster experience construction. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table 8: Disasters and enrollments, heterogeneities across country and age groups

	(1)	(2)
Had disaster in most recent 12 mo.		
× Pakistan		−0.104*
		(0.055)
× Age 5–8	−0.105*	
	(0.056)	
× Age 9–12	−0.110**	
	(0.055)	
× Age 13–17	−0.101*	
	(0.058)	
× Bangladesh		0.001
		(0.009)
× Age 5–8	0.044***	
	(0.014)	
× Age 9–12	−0.011	
	(0.008)	
× Age 13–17	−0.027**	
	(0.012)	
× Others		−0.009
		(0.006)
× Age 5–8	−0.005	
	(0.008)	
× Age 9–12	−0.013*	
	(0.007)	
× Age 13–17	−0.013	
	(0.010)	
# of mo. with disaster in the first 1,000 days		
× Pakistan		−0.001
		(0.001)
× Age 5–8	−0.006**	
	(0.003)	
× Age 9–12	−0.001	
	(0.001)	
× Age 13–17	−0.001	
	(0.002)	
× Bangladesh		−0.005***
		(0.001)
× Age 5–8	0.003	
	(0.002)	
× Age 9–12	−0.002**	
	(0.001)	
× Age 13–17	−0.003***	
	(0.001)	
× Others		0.001***
		(0.000)
× Age 5–8	0.002***	
	(0.000)	
× Age 9–12	−0.000	
	(0.000)	
× Age 13–17	−0.001	
	(0.001)	
Observations	143,645	143,645

Note: This table shows heterogeneity analysis across countries and ages for disaster effects on enrollments. This corresponds with Eq. (2), with interacting disaster shocks between age groups and country groups. In Pakistan, 61% of children in each age group have experienced natural disasters in the most recent 12 months. The share is higher for Bangladesh (72%) but also about the same across age groups. It is much lower for children in other countries (26%). For the early life disasters, in Pakistan, children aged 5–8, 9–12, and 13–17 have on average 1, 2, and 4 months with disasters, respectively. The share is higher for Bangladesh, as children aged 5–8, 9–12, and 13–17 experienced disaster for 2, 4, and 5 months during the first 1,000 days, respectively. In other countries, children aged 5–8 and 9–12 have on average 3.5 months with disasters, while children aged 13–17 have experienced 1.7 months of disasters. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table 9: Disasters and math scores, heterogeneities across gender and age groups

	(1) All disasters	(2) Floods	(3) Severe disasters	(4) Severe floods
# of mo. with disaster in mid-child life				
× Male				
× Age 7–9	−0.037	0.013	−0.011	0.073
	(0.024)	(0.052)	(0.042)	(0.064)
× Age 10–12	−0.023	−0.011	−0.014	0.047
	(0.023)	(0.044)	(0.028)	(0.054)
× Age 13–14	−0.026	−0.044	−0.034	0.010
	(0.022)	(0.040)	(0.027)	(0.050)
× Female				
× Age 7–9	−0.004	0.018	0.003	0.067
	(0.026)	(0.052)	(0.040)	(0.066)
× Age 10–12	−0.006	−0.060	−0.021	−0.010
	(0.023)	(0.044)	(0.027)	(0.051)
× Age 13–14	−0.007	−0.017	−0.016	0.032
	(0.022)	(0.037)	(0.026)	(0.046)
# of mo. with disaster in the first 1,000 days				
× Male				
× Age 7–9	−0.036	−0.095*	−0.047	−0.070
	(0.027)	(0.053)	(0.031)	(0.060)
× Age 10–12	0.015	−0.003	0.011	−0.031
	(0.021)	(0.032)	(0.029)	(0.047)
× Age 13–14	−0.018	−0.008	−0.031	−0.025
	(0.031)	(0.045)	(0.038)	(0.052)
× Female				
× Age 7–9	−0.041**	−0.076	−0.015	−0.035
	(0.021)	(0.059)	(0.030)	(0.063)
× Age 10–12	0.012	0.004	0.023	0.028
	(0.019)	(0.033)	(0.025)	(0.046)
× Age 13–14	−0.041*	−0.037	−0.023	−0.054
	(0.024)	(0.040)	(0.035)	(0.050)
Observations	78,303	78,303	78,303	78,303
Within-country location FE	Y	Y	Y	Y
Interview year FE	Y	Y	Y	Y
Interview month FE	Y	Y	Y	Y
Child age FE	Y	Y	Y	Y
Attainment t × country FE	Y	Y	Y	Y

Note: This table shows heterogeneity analyses across gender and ages for disaster effects on math-test scores. This corresponds to Eq. (3), with interacting disaster shocks between age groups and gender. The first 1,000 days is defined as the period from conception to 24 months of age in child development; hence, in total, there are 33 months in the period. The mid-child life is defined as the period between the first 1,000 days and two years prior to the survey month. The average number of months covered in mid-child life is 53 months, 90 months, and 120 months for children aged 7–9, 10–12, and 13–14, respectively. For both boys and girls in each age group, about 56% have experienced a natural disaster in the most recent 12 months. The average number of months with a disaster in the first 1,000 days for children of both genders aged 7–9, 10–12, and 13–14 is about 2 months, 3 months, and 4 months, respectively. The average number of months with a disaster in mid-child life is about 5.4 months, 8 months, and 10.5 months for children aged 7–9, 10–12, and 13–14, respectively; this does not vary across genders. The average math-test score for boys aged 7 to 9 is 12.4 (standard deviation is 7.6), which is slightly higher than that of girls (12.1). The average math-test score for boys aged 9 to 12 is 15.4, and the standard deviation is 7. Girls are observed to have an average math score of 15. For the oldest group of children, aged 13 to 14, the average math-test scores are 16 for boys (standard deviation is 6.6) and 15.6 for girls (standard deviation is 7). The distribution of math-test scores across ages and countries is shown in Figure 3. For the disaster intensity type, we consider all disasters, only floods, severe disasters (defined as causing more than 500 casualties or affecting at least 5,000 people), and only severe floods. Having various disaster intensity types provides the possibility for robustness checks on disaster experience construction. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

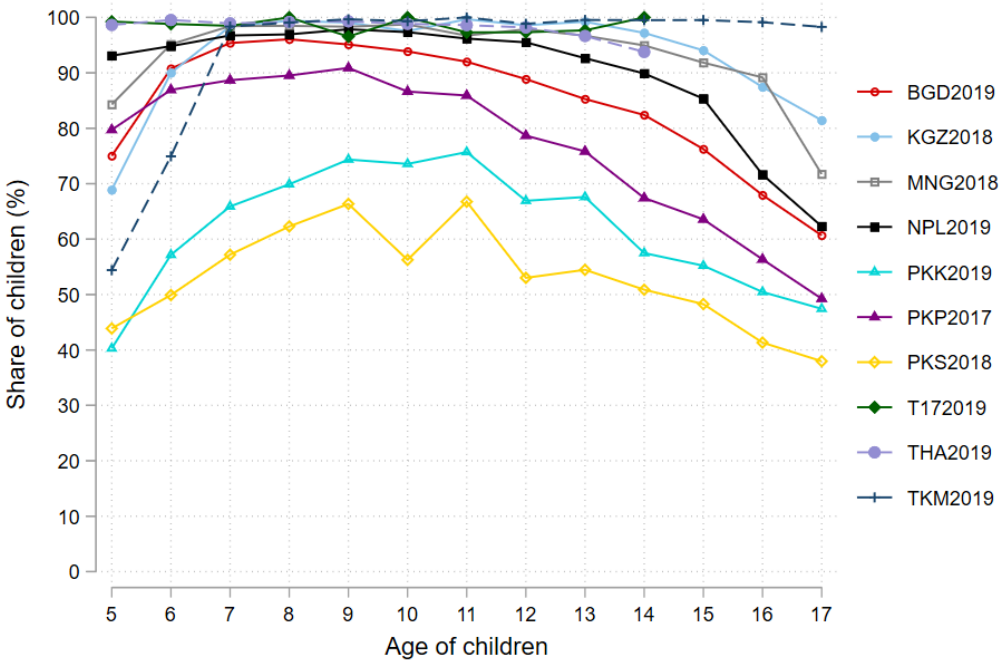
Table 10: Disasters and math scores, heterogeneity across country and age groups

	(1)	(2)
# of mo. with disaster in mid-child life		
× Pakistan		−0.004
		(0.023)
× Age 7–9	−0.045	
	(0.070)	
× Age 10–12	−0.124**	
	(0.050)	
× Age 13–14	−0.054	
	(0.037)	
× Bangladesh		−0.054**
		(0.024)
× Age 7–9	−0.153***	
	(0.057)	
× Age 10–12	−0.030	
	(0.030)	
× Age 13–14	−0.065**	
	(0.029)	
× Others		0.034
		(0.027)
× Age 7–9	0.031	
	(0.042)	
× Age 10–12	0.032	
	(0.040)	
× Age 13–14	0.032	
	(0.042)	
# of mo. with disaster in the first 1,000 days		
× Pakistan		−0.093***
		(0.020)
× Age 7–9	−0.198***	
	(0.065)	
× Age 10–12	−0.013	
	(0.024)	
× Age 13–14	−0.090	
	(0.056)	
× Bangladesh		0.025
		(0.031)
× Age 7–9	0.075	
	(0.057)	
× Age 10–12	0.038	
	(0.032)	
× Age 13–14	−0.012	
	(0.031)	
× Others		0.033
		(0.030)
× Age 7–9	0.017	
	(0.029)	
× Age 10–12	0.040	
	(0.034)	
× Age 13–14	0.086***	
	(0.032)	
Observations	78,303	78,303

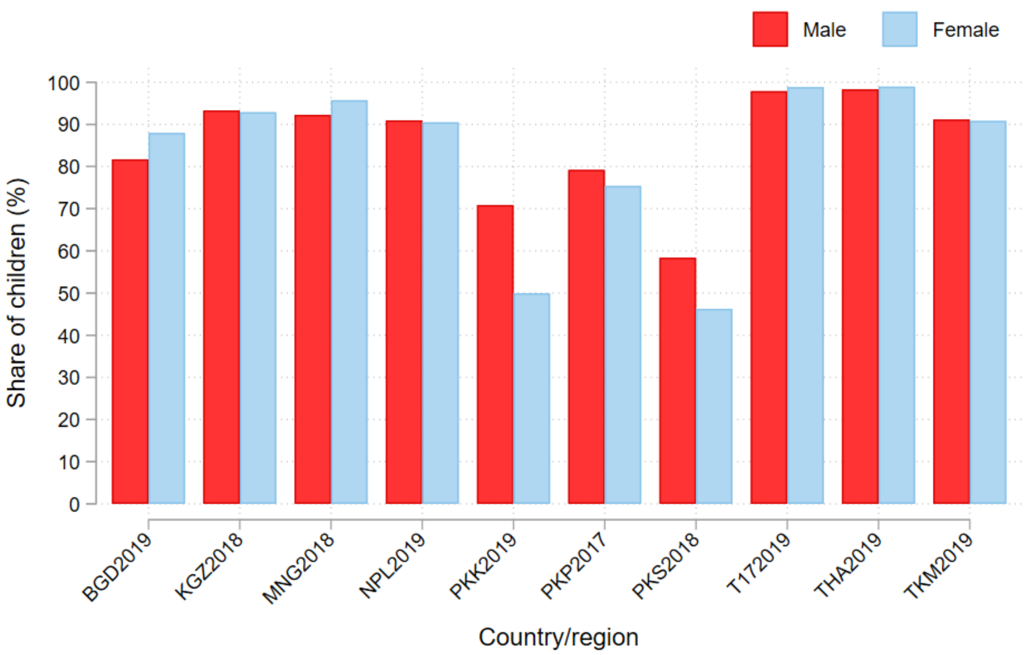
Note: This table shows heterogeneity analysis across countries and ages of disaster effects on math scores. This corresponds with Eq. (3), with interactions between disaster shocks, age groups, and country groups. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Figure 1: Enrollment Fractions in Survey Year

(a) Enrollment Fractions in Survey Years by Age and Country



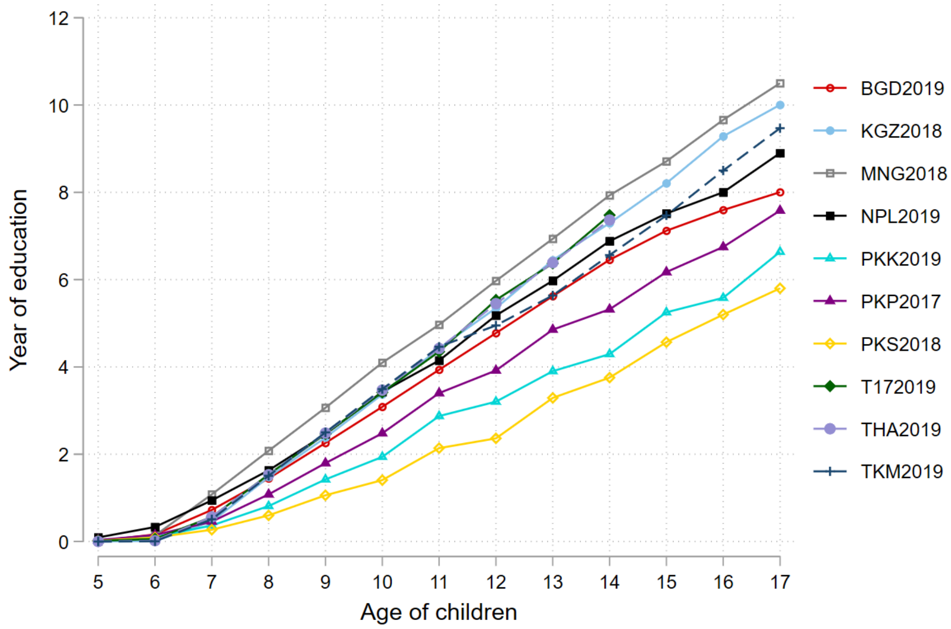
(b) Enrollment Fractions in Survey Years by Gender and Country



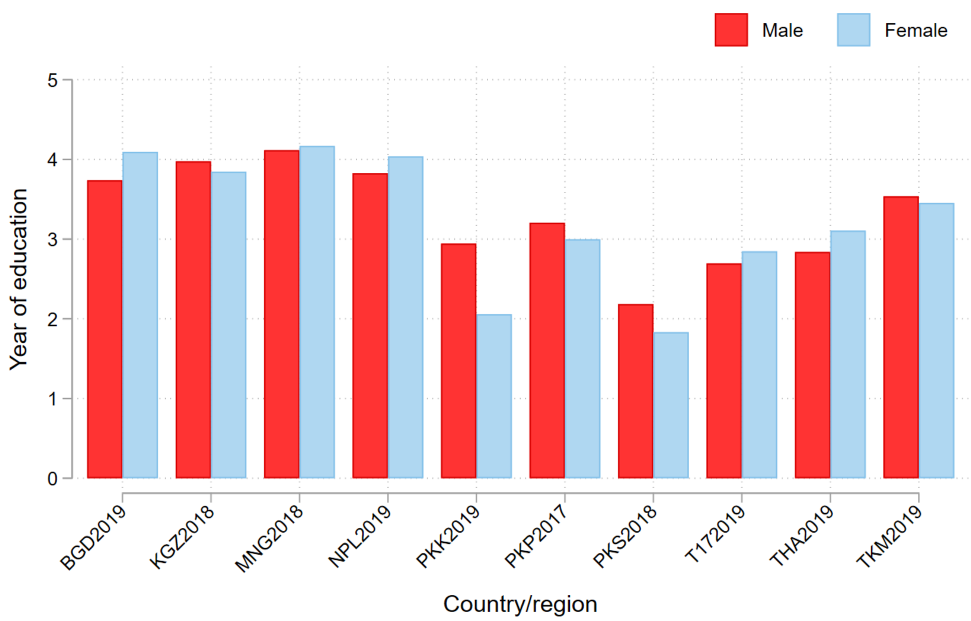
Note: Enrollment fractions in survey years. In Thailand, data are observed only up to age 14; in all other countries, data are available up to age 17. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure 2: Average Attainments Completed by Age and Country

(a) Average Attainments Completed by Age and Country



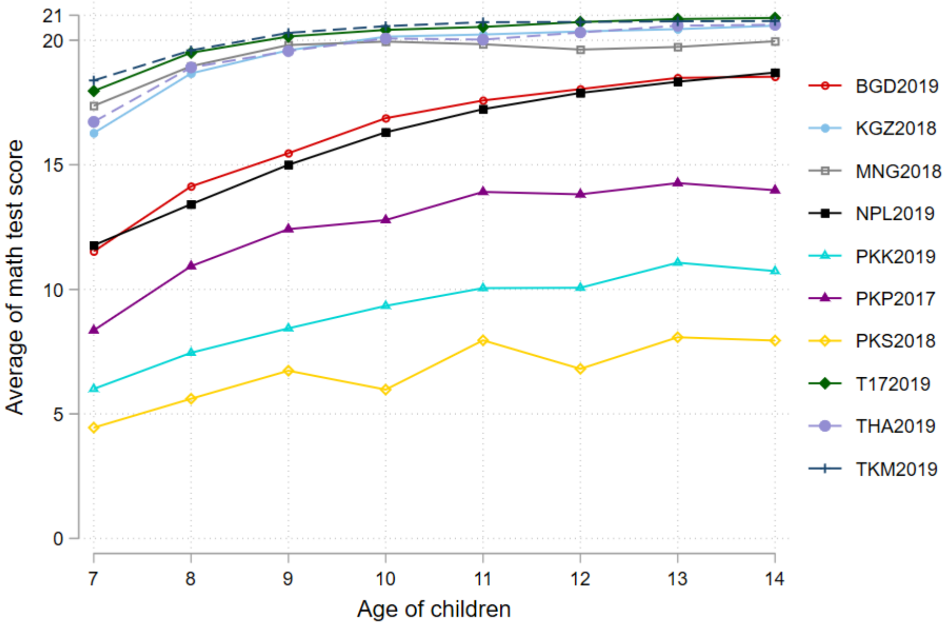
(b) Average Attainments Completed by Gender and Country



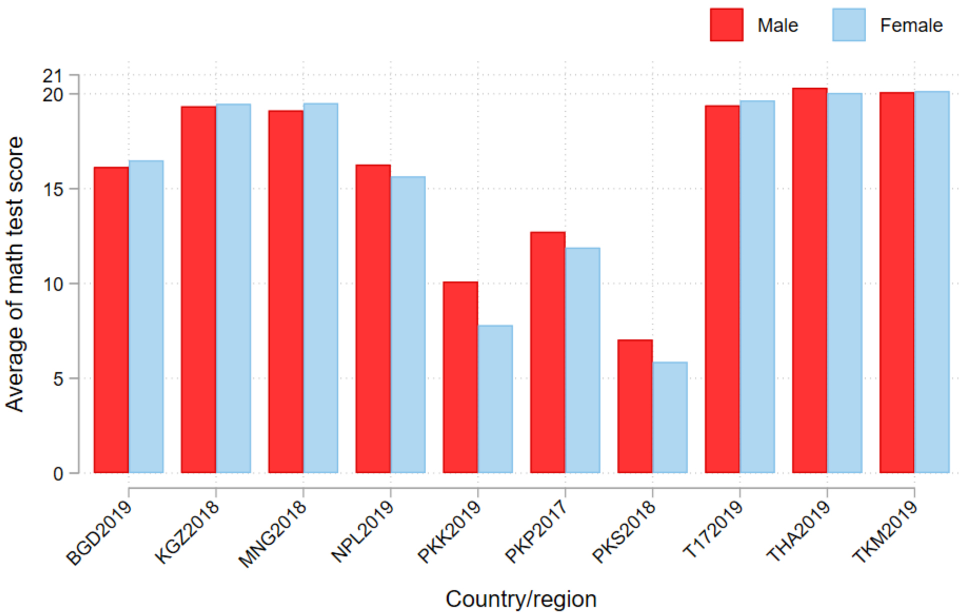
Note: In Thailand, data are observed only up to age 14; in all other countries, data are available up to age 17. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).The grades of schooling completed is calculated based on the educational level and grade, as well as the country-specific educational system for each child enrolled at the start of the last school year, at the start of this school year, and before the survey month. This figure presents the average years of schooling completed at the start of this school year.

Figure 3: Distribution of Math Scores

(a) Average of Math Scores by Age and Country

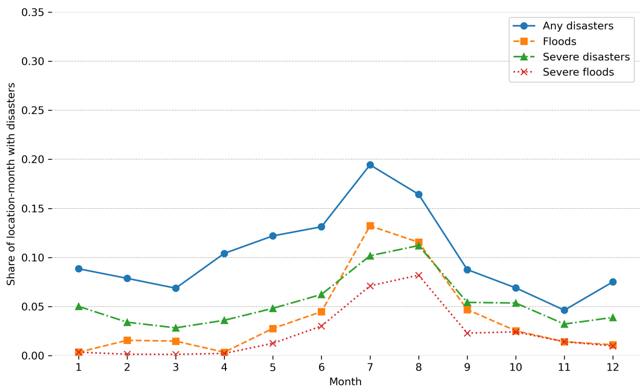


(b) Average of Math Scores by Gender and Country (Ages 7–14)

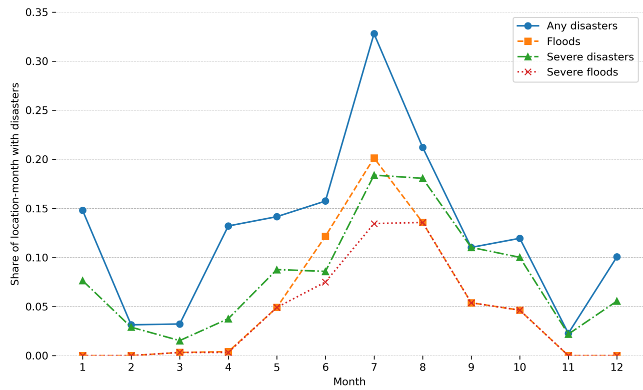


Note: Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

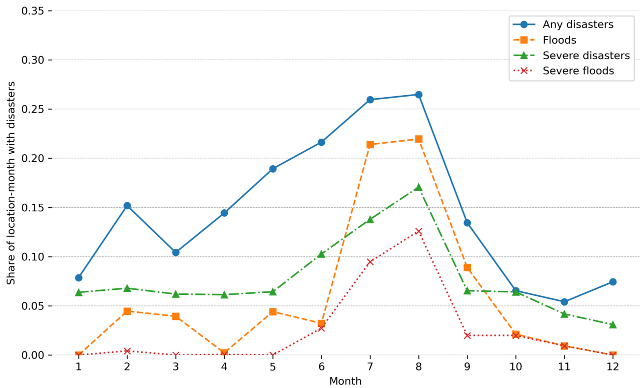
Figure 4: Share of Location-Months with Disasters in Each Calendar Month over 20 Years



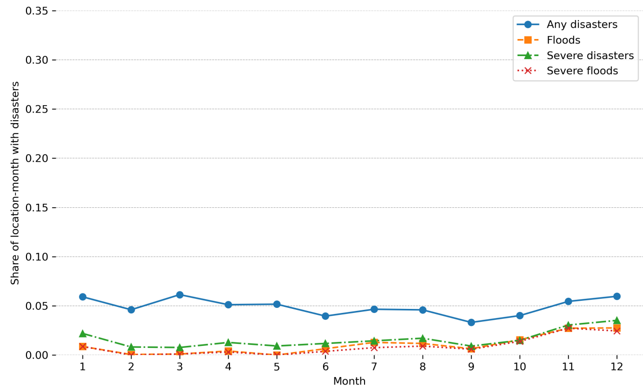
(a) All Countries



(b) Bangladesh Only



(c) Pakistan Only



(d) Other Countries

Note: For each location in every month from the latest survey month to 20 years prior to the survey, we construct a disaster indicator using EM-DAT data. For all locations in the previous 20 years, the share of location-months with disaster shocks of each type is shown across the calendar months of the year.

References

Alam, Shamma Adeeb. 2015. "Parental Health Shocks, Child Labor and Educational Outcomes: Evidence from Tanzania." *Journal of Health Economics* 44 (December): 161–175. https://doi.org/10.1016/j.jhealeco.2015.09.004.

Alban Conto, Carolina, Spogmai Akseer, Thomas Dreesen, Akito Kamei, Suguru Mizunoya, and Annika Rigole. 2021. "Potential Effects of COVID-19 School Closures on Foundational Skills and Country Responses for Mitigating Learning Loss." *International Journal of Educational Development* 87 (November 1, 2021): 102434. https://doi.org/10.1016/j.ijedudev.2021.102434.

Alderman, Harold, and Paul Gertler. 1997. "Family Resources and Gender Differences in Human Capital Investments: The Demand for Children's Medical Care in Pakistan." *Intrahousehold Resource Allocation in Developing Countries* 231 (48).

Almond, Douglas, Janet Currie, and Valentina Duque. 2018. "Childhood Circumstances and Adult Outcomes: Act II." *Journal of Economic Literature* 56, no. 4 (December): 1360–1446. https://doi.org/10.1257/jel.20171164.

Almond, Douglas, Lena Edlund, and Mårten Palme. 2009. "Chernobyl's Subclinical Legacy: Prenatal Exposure to Radioactive Fallout and School Outcomes in Sweden*." *The Quarterly Journal of Economics* 124, no. 4 (November): 1729–1772. https://doi.org/10.1162/qjec.2009.124.4.1729.

Almond, Douglas, and Bhashkar Mazumder. 2005. "The 1918 Influenza Pandemic and Subsequent Health Outcomes: An Analysis of SIPP Data." *American Economic Review* 95, no. 2 (May): 258–262. https://doi.org/10.1257/000282805774669943.

Amouzou, Agbessi, Vrinda Mehra, Liliana Carvajal–Aguirre, Shane M. Khan, Deborah Sitrin, and Lara ME Vaz. 2017. "Measuring Postnatal Care Contacts for Mothers and Newborns: An Analysis of Data from the MICS and DHS Surveys." *Journal of Global Health* 7, no. 2 (December 20, 2017): 020502. https://doi.org/10.7189/jogh.07.020502.

Andrabi, Tahir, Benjamin Daniels, and Jishnu Das. 2021. "Human Capital Accumulation and Disasters: Evidence from the Pakistan Earthquake of 2005." *Journal of Human Resources* (June). https://doi.org/10.3368/jhr.59.2.0520-10887R1.

Angrist, Noam, Micheal Ainomugisha, Sai Pramod Bathena, Peter Bergman, Colin Crossley, Claire Cullen, Thato Letsomo, et al. 2023. *Building Resilient Education Systems: Evidence from Large-Scale Randomized Trials in Five Countries,* 31208, May. https://doi.org/10.3386/w31208.

Attanasio, Orazio P., Costas Meghir, and Ana Santiago. 2012. "Education Choices in Mexico: Using a Structural Model and a Randomized Experiment to Evaluate PROGRESA." *The Review of Economic Studies* 79, no. 1 (January 1, 2012): 37–66. https://doi.org/10.1093/restud/rdr015.

Baez, Javier E, and Indhira V Santos. 2007. "Children's Vulnerability to Weather Shocks: A Natural Disaster as a Natural Experiment." *IZA Working Paper.*

Bandara, Amarakoon, Rajeev Dehejia, and Shaheen Lavie-Rouse. 2015. "The Impact of Income and Non-Income Shocks on Child Labor: Evidence from a Panel Survey of Tanzania." *World Development* 67 (March): 218–237. https://doi.org/10.1016/j.worlddev.2014.10.019.

Bangladesh Bureau of Statistics (BBS) and UNICEF Bangladesh. 2019. "Progotir Pathey, Bangladesh Multiple Indicator Cluster Survey 2019, Survey Findings Report." *Dhaka, Bangladesh: Bangladesh Bureau of Statistics (BBS).*

Behrman, Jere. 2015. "Growth Faltering in the First Thousand Days after Conception and Catch-up Growth." In *The Oxford Handbook of Economics and Human Biology,* 9–31. Oxford University Press, October. https://doi.org/10.1093/oxfordhb/9780199389292.013.28.

Behrman, Jere R, Anil B Deolalikar, and Pranee Tinakorn. 2001. "The effects of the Thai economic crisis and of Thai labor market policies on labor market outcomes: executive summary." *TDRI Quarterly Review* 16 (3): 3–9.

Behrman, Jere R. 1988. "Intrahousehold Allocation of Nutrients in Rural India: Are Boys Favored? Do Parents Exhibit Inequality Aversion?" *Oxford Economic Papers* 40, no. 1 (March): 32–54. https://doi.org/10.1093/oxfordjournals.oep.a041845.

Behrman, Jere R., and Anil B. Deolalikar. 1990. "The Intrahousehold Demand for Nutrients in Rural South India: Individual Estimates, Fixed Effects, and Permanent Income." *The Journal of Human Resources* 25 (4): 665–696. https://doi.org/10.2307/145671.

Black, Robert E., Li Liu, Fernando P. Hartwig, Francisco Villavicencio, Andrea Rodriguez-Martinez, Luis P. Vidaletti, Jamie Perin, et al. 2022. "Health and Development from Preconception to 20 Years of Age and Human Capital." *The Lancet* 399, no. 10336 (April): 1730–1740. https://doi.org/10.1016/S0140-6736(21)02533-2.

Botzen, W. J. W., J. C. J. H. Aerts, and J. C. J. M. van den Bergh. 2009. "Dependence of flood risk perceptions on socioeconomic and objective risk factors." *Water Resources Research* 45 (10). https://doi.org/10.1029/2009WR007743.

Botzen, W. J. Wouter, Olivier Deschenes, and Mark Sanders. 2019. "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies." *Review of Environmental Economics and Policy* 13, no. 2 (July): 167–188. https://doi.org/10.1093/reep/rez004.

Boustan, Leah Platt, Matthew E. Kahn, Paul W. Rhode, and Maria Lucia Yanguas. 2020. "The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data." *Journal of Urban Economics* 118 (July): 103257. https://doi.org/10.1016/j.jue.2020.103257.

Bureau of Statistics, Government of Khyber Pakhtunkhwa, Planning & Development Department. 2021. "Khyber Pakhtunkhwa Multiple Indicator Cluster Survey, 2019, Survey Findings Report." *Peshawar, Pakistan: Bureau of Statistics, Planning & Development Department, Government of Khyber Pakhtunkhwa.*

Cadag, Jake Rom D., Marla Petal, Emmanuel Luna, J. C. Gaillard, Lourdes Pambid, and Genia V. Santos. 2017. "Hidden disasters: Recurrent flooding impacts on educational continuity in the Philippines." *International Journal of Disaster Risk Reduction* 25 (October 1, 2017): 72–81. https://doi.org/10.1016/j.ijdrr.2017.07.016.

Cameron, Lisa A., and Christopher Worswick. 2001. "Education Expenditure Responses to Crop Loss in Indonesia: A Gender Bias." *Economic Development and Cultural Change* 49, no. 2 (January): 351–363. https://doi.org/10.1086/452506.

Caruso, Germán Daniel. 2017. "The Legacy of Natural Disasters: The Intergenerational Impact of 100 Years of Disasters in Latin America." *Journal of Development Economics* 127 (July): 209–233. https://doi.org/10.1016/j.jdeveco.2017.03.007.

Cas, Ava Gail, Elizabeth Frankenberg, Wayan Suriastini, and Duncan Thomas. 2014. "The Impact of Parental Death on Child Well-being: Evidence From the Indian Ocean Tsunami." *Demography* 51, no. 2 (February 27, 2014): 437–457. https://doi.org/10.1007/s13524-014-0279-8.

Casco, José L. 2022. "Household Choices of Child Activities in the Presence of Cash Transfers." *Journal of Economic Behavior & Organization* 196 (April 1, 2022): 524–545. https://doi.org/10.1016/j.jebo.2022.02.017.

Case, Anne, and Christina Paxson. 2010. "Causes and Consequences of Early-Life Health." *Demography* 47, no. 1 (March): S65–S85. https://doi.org/10.1353/dem.2010.0007.

Chang, Grace, Marta Favara, and Rafael Novella. 2022. "The Origins of Cognitive Skills and Non-cognitive Skills: The Long-Term Effect of In-Utero Rainfall Shocks in India." *Economics & Human Biology* 44 (January 1, 2022): 101089. https://doi.org/10.1016/j.ehb.2021.101089.

Chang, Muhammad Saleem, Shahneela, Zohra Khatoon, and Syed Shah Bukhari. 2013. "Flood Disasters and Its Impacts on Child Education in Sindh (A Case Study of 2010 Flood)." *International Journal of Advanced Research* 1 (May 13, 2013): 329–344.

Charil, Arnaud, David P. Laplante, Cathy Vaillancourt, and Suzanne King. 2010. "Prenatal Stress and Brain Development." *Brain Research Reviews* 65, no. 1 (October): 56–79. https://doi.org/10.1016/j.brainresrev.2010.06.002.

Cho, Hyunkuk, and Hwanyeon Kim. 2023. "Stress and Cognitive Performance: Evidence from a South Korean Earthquake." *Education Finance and Policy* (April 24, 2023): 1–19. https://doi.org/10.1162/edfp_a_00393.

Ciancio, Alberto, Jere Behrman, Fabrice Kämpfen, Iliana V. Kohler, Jürgen Maurer, Victor Mwapasa, and Hans-Peter Kohler. 2023. "Barker's Hypothesis Among the Global Poor: Positive Long-Term Cardiovascular Effects of In Utero Famine Exposure." *Demography* 60, no. 6 (December 1, 2023): 1747–1766. https://doi.org/10.1215/00703370-11052790.

Ciraudo, Martha. 2020. "The Relationship Between Prenatal Stress Due to Natural Disasters and the Long-Term Educational Achievement of Chilean Students." ALM, Harvard University.

Comprehensive Disaster Management Programme, Bangladesh. 2015. "National Strategy on the Management of Disaster and Climate Induced Internal Displacement." *Dhaka: Ministry of Disaster Management and Relief.*

Cunha, Flavio, James J. Heckman, Lance Lochner, and Dimitriy V. Masterov. 2006. "Chapter 12 Interpreting the Evidence on Life Cycle Skill Formation." In *Handbook of the Economics of Education,* 1:697–812. Elsevier. https://doi.org/10.1016/S1574-0692(06)01012-9.

Currie, Janet, and Maya Rossin-Slater. 2013. "Weathering the Storm: Hurricanes and Birth Outcomes." *Journal of Health Economics* 32, no. 3 (May): 487–503. https://doi.org/10.1016/j.jhealeco.2013.01.004.

De Vreyer, Philippe, Nathalie Guilbert, and Sandrine Mesple-Somps. 2015. "Impact of Natural Disasters on Education Outcomes: Evidence from the 1987–89 Locust Plague in Mali†."

Journal of African Economies 24, no. 1 (January 1, 2015): 57–100. https://doi.org/10.1093/jae/eju018.

Delforge, Damien, Valentin Wathelet, Regina Below, Cinzia Lanfredi Sofia, Margo Tonnelier, Joris Van Loenhout, and Niko Speybroeck. 2023. *EM-DAT: The Emergency Events Database,* December. https://doi.org/10.21203/rs.3.rs-3807553/v1.

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

Doyle, Orla. 2020. "The First 2,000 Days and Child Skills." *Journal of Political Economy* 128, no. 6 (June): 2067–2122. https://doi.org/10.1086/705707.

Drèze, Jean, and Amartya Sen. 1991. *Hunger and Public Action.* 1st ed. Oxford University Press, January. https://doi.org/10.1093/0198283652.001.0001.

UN-ESCAP, United Nations Economic and Social Commission for Asia and the Pacific. 2023. "Seizing the Moment : Targeting Transformative Disaster Risk Resilience." *Asia Pacific Disaster Report (APDR)* Area(s) of Work Building Resilience to Disasters (SDG 13. Climate Action 2023). https://doi.org/10.18356/25206796-2020-13.

Felbermayr, Gabriel, and Jasmin Gröschl. 2014. "Naturally Negative: The Growth Effects of Natural Disasters." *Journal of Development Economics,* Special Issue: Imbalances in Economic Development, 111 (November): 92–106. https://doi.org/10.1016/j.jdeveco.2014.07.004.

Fuller, Sarah C. 2014. "The Effect of Prenatal Natural Disaster Exposure on School Outcomes." *Demography* 51, no. 4 (June 6, 2014): 1501–1525. https://doi.org/10.1007/s13524-014-0310-0.

Gertler, Paul, James Heckman, Rodrigo Pinto, Arianna Zanolini, Christel Vermeersch, Susan Walker, Susan M. Chang, et al. 2014. "Labor Market Returns to an Early Childhood Stimulation Intervention in Jamaica." *Science* 344, no. 6187 (May): 998–1001. https://doi.org/10.1126/science.1251178.

Gibbs, Lisa, Jane Nursey, Janette Cook, Greg Ireton, Nathan Alkemade, Michelle Roberts, H. Colin Gallagher, et al. 2019. "Delayed Disaster Impacts on Academic Performance of Primary School Children." *Child Development* 90 (4): 1402–1412. https://doi.org/10.1111/cdev.13200.

Gitter, Seth R., and Bradford L. Barham. 2007. "Credit, Natural Disasters, Coffee, and Educational Attainment in Rural Honduras." *World Development* 35, no. 3 (March 1, 2007): 498–511. https://doi.org/10.1016/j.worlddev.2006.03.007.

Glewwe, Paul, Hanan G Jacoby, and Elizabeth M King. 2001. "Early Childhood Nutrition and Academic Achievement: A Longitudinal Analysis." *Journal of Public Economics* 81, no. 3 (September): 345–368. https://doi.org/10.1016/S0047-2727(00)00118-3.

Glewwe, Paul, and Elizabeth M. King. 2001. "The Impact of Early Childhood Nutritional Status on Cognitive Development: Does the Timing of Malnutrition Matter?" *The World Bank Economic Review* 15, no. 1 (June): 81–113. https://doi.org/10.1093/wber/15.1.81.

Gochyyev, P, S Mizunoya, and M Cardoso. 2019. "Validity and Reliability of the MICS Foundational Learning Module (MICS Methodological Papers, No. 9, Data and Analytics Section, Division of Data, Research and Policy)." *New York: UNICEF.*

Grantham-McGregor, Sally, Yin Bun Cheung, Santiago Cueto, Paul Glewwe, Linda Richter, and Barbara Strupp. 2007. "Developmental Potential in the First 5 Years for Children in Developing Countries." *The Lancet* 369, no. 9555 (January): 60–70. https://doi.org/10.1016/S0140-6736(07)60032-4.

Guarcello, Lorenzo, Fabrizia Mealli, and Furio Camillo Rosati. 2010. "Household Vulnerability and Child Labor: The Effect of Shocks, Credit Rationing, and Insurance." *Journal of Population Economics* 23, no. 1 (January): 169–198. https://doi.org/10.1007/s00148-008-0233-4.

Gunnsteinsson, Snaebjorn, Achyuta Adhvaryu, Parul Christian, Alain Labrique, Jonathan Sugimoto, Abu Ahmed Shamim, and Keith P West. 2015. "Vitamin A and Resilience to Early Life Shocks." *Working Paper.*

Gupta, Monica Das. 1987. "Selective Discrimination Against Female Children in Rural Punjab, India." *Population and Development Review* 13 (1): 77–100. https://doi.org/10.2307/1972121.

Hadiman, Rizki, and Sartika Djamaluddin. 2022. "Impact of Earthquake on Human Capital Formation." *Economics Development Analysis Journal* 11, no. 1 (March 18, 2022): 75–95.

Hanushek, Eric A., and Steven G. Rivkin. 2012. "The Distribution of Teacher Quality and Implications for Policy." *Annual Review of Economics* 4 (1): 131–157. https://doi.org/10.1146/annurev-economics-080511-111001.

Hirvonen, Kalle, Thomas Pave Sohnesen, and Tom Bundervoet. 2020. "Impact of Ethiopia's 2015 Drought on Child Undernutrition." *World Development* 131 (July): 104964. https://doi.org/10.1016/j.worlddev.2020.104964.

Hoddinott, John, Jere R Behrman, John A Maluccio, Paul Melgar, Agnes R Quisumbing, Manuel Ramirez-Zea, Aryeh D Stein, et al. 2013. "Adult Consequences of Growth Failure in Early Childhood." *The American Journal of Clinical Nutrition* 98, no. 5 (November): 1170–1178. https://doi.org/10.3945/ajcn.113.064584.

Hoddinott, John, John A Maluccio, Jere R Behrman, Rafael Flores, and Reynaldo Martorell. 2008. "Effect of a Nutrition Intervention During Early Childhood on Economic Productivity in Guatemalan Adults." *The Lancet* 371, no. 9610 (February): 411–416. https://doi.org/10.1016/S0140-6736(08)60205-6.

Huang, Zenghe, and Xiaofang Dong. 2025. "When the levee breaks: The impact of floods on educational outcomes in China." *Journal of Development Economics* 174 (May 1, 2025): 103450. https://doi.org/10.1016/j.jdeveco.2025.103450.

INEE, (Inter-agency Network for Education in Emergencies). 2024. *Minimum Standards for Education: Preparedness, Response, Recovery.* 2024 Edition. INEE.

Intergovernmental Panel On Climate Change, ed. 2014. *Climate Change 2013 – The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* 1st ed. Cambridge University Press, March. https://doi.org/10.1017/CBO9781107415324.

Intergovernmental Panel on Climate Change. 2022. *Global Warming of 1.5°C: IPCC Special Report on Impacts of Global Warming of 1.5°C above Pre-industrial Levels in Context of Strengthening Response to Climate Change, Sustainable Development, and Efforts to*

Eradicate Poverty. Cambridge: Cambridge University Press. https://doi.org/10.1017/9781009157940.

Jansuttipan, Monruedee. 2022. "Cleaning up and caring for communities after a disaster." UNICEF Thailand, February 24, 2022. https://www.unicef.org/thailand/stories/cleaning-and-caring-communities-after-disaster.

Jayachandran, Seema. 2009. "Air Quality and Early-Life Mortality: Evidence from Indonesia's Wildfires." *Journal of Human Resources* 44, no. 4 (October): 916–954. https://doi.org/10.3368/jhr.44.4.916.

Kahn, Matthew E. 2005. "The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions." *The Review of Economics and Statistics* 87, no. 2 (May): 271–284. https://doi.org/10.1162/0034653053970339.

Klomp, Jeroen, and Kay Valckx. 2014. "Natural Disasters and Economic Growth: A Meta-analysis." *Global Environmental Change* 26 (May): 183–195. https://doi.org/10.1016/j.gloenvcha.2014.02.006.

Kousky, Carolyn. 2016. "Impacts of Natural Disasters on Children." *The Future of Children* 26 (1): 73–92.

Lazzaroni, Sara, and Peter A. G. van Bergeijk. 2014. "Natural Disasters' Impact, Factors of Resilience and Development: A Meta-analysis of the Macroeconomic Literature." *Ecological Economics* 107 (November): 333–346. https://doi.org/10.1016/j.ecolecon.2014.08.015.

Leiter, Andrea M., Harald Oberhofer, and Paul A. Raschky. 2009. "Creative Disasters? Flooding Effects on Capital, Labour and Productivity Within European Firms." *Environmental and Resource Economics* 43, no. 3 (July): 333–350. https://doi.org/10.1007/s10640-009-9273-9.

Lin, Ming-Jen, and Elaine M. Liu. 2014. "Does In Utero Exposure to Illness Matter? The 1918 Influenza Epidemic in Taiwan as a Natural Experiment." *Journal of Health Economics* 37 (September): 152–163. https://doi.org/10.1016/j.jhealeco.2014.05.004.

Liu, Elaine M, Jin-Tan Liu, and Tzu-Yin Hazel Tseng. 2022. "The Impact of a Natural Disaster on the Incidence of Fetal Losses and Pregnancy Outcomes." *Working Paper.*

Maccini, Sharon, and Dean Yang. 2009. "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall." *American Economic Review* 99, no. 3 (June): 1006–1026. https://doi.org/10.1257/aer.99.3.1006.

Maluccio, John A., John F. Hoddinott, Jere R. Behrman, Agnes R. Quisumbing, Reynaldo Martorell, and Aryeh D. Stein. 2009. "The Impact of Improving Nutrition During Early Childhood on Education among Guatemalan Adults." *Economic Journal* 119 (537): 734–763.

Mavhura, Emmanuel, and Komal Raj Aryal. 2023. "Disaster Mortalities and the Sendai Framework Target A: Insights from Zimbabwe." *World Development* 165 (May): 106196. https://doi.org/10.1016/j.worlddev.2023.106196.

McCoy, Dana C., Jorge Cuartas, Jere Behrman, Claudia Cappa, Jody Heymann, Florencia López Bóo, Chunling Lu, et al. 2021. "Global Estimates of the Implications of COVID-19-related Preprimary School Closures for Children's Instructional Access, Development, Learning, and Economic Wellbeing." *Child Development* 92, no. 5 (September): e883–e899. https://doi.org/10.1111/cdev.13658.

National Disaster Management Authority (Pakistan), Pakistan - government. 2017. "Pakistan: School safety framework." PreventionWeb. https://www.preventionweb.net/publication/pakistan-school-safety-framework.

National Institute of Population Studies, (NIPS) [Pakistan], and ICF. 2019. "2017-18 Pakistan Demographic and Health Survey Key Findings." Islamabad, Pakistan, and Rockville, Maryland, USA: NIPS and ICF. https://www.dhsprogram.com/pubs/pdf/SR257/SR257.pdf.

Noy, Ilan. 2009. "The Macroeconomic Consequences of Disasters." *Journal of Development Economics* 88, no. 2 (March): 221–231. https://doi.org/10.1016/j.jdeveco.2008.02.005.

Nübler, Laura, Karen Austrian, John A. Maluccio, and Jessie Pinchoff. 2021. "Rainfall Shocks, Cognitive Development and Educational Attainment among Adolescents in a Drought-prone Region in Kenya." *Environment and Development Economics* 26, nos. 5-6 (October): 466–487. https://doi.org/10.1017/S1355770X20000406.

Opper, Isaac M., R. Jisung Park, and Lucas Husted. 2023. "The Effect of Natural Disasters on Human Capital in the United States." *Nature Human Behaviour* 7, no. 9 (September): 1442–1453. https://doi.org/10.1038/s41562-023-01610-z.

Panwar, Vikrant, and Subir Sen. 2020. "Disaster Damage Records of EM-DAT and DesInventar: A Systematic Comparison." *Economics of Disasters and Climate Change* 4, no. 2 (July 1, 2020): 295–317. https://doi.org/10.1007/s41885-019-00052-0.

Pazos, Nicolás, Marta Favara, Alan Sánchez, Douglas Scott, and Jere Behrman. 2024. "Long-term effects of early life rainfall shocks on foundational cognitive skills: Evidence from Peru." *Economics & Human Biology* 54:101407.

Raeburn, Kaywana. 2023. "The Effect of School Damages on Educational Outcomes in Post-Hurricane Jamaica." *Education Economics* 0, no. 0 (December 5, 2023): 1–23. https://doi.org/10.1080/09645292.2023.2289345.

Randell, Heather, Clark Gray, and Kathryn Grace. 2020. "Stunted from the Start: Early Life Weather Conditions and Child Undernutrition in Ethiopia." *Social Science & Medicine* 261 (September): 113234. https://doi.org/10.1016/j.socscimed.2020.113234.

Raza, Syed Hassan, Zulfiqar Ali Shah, and Wajiha Haq. 2022. "Role of Birth Order, Gender, and Region in Educational Attainment in Pakistan." *Scientific Reports* 12, no. 1 (July): 11842. https://doi.org/10.1038/s41598-022-15700-x.

Rondó, P. H. C., R. F. Ferreira, F. Nogueira, M. C. N. Ribeiro, H. Lobert, and R. Artes. 2003. "Maternal Psychological Stress and Distress as Predictors of Low Birth Weight, Prematurity and Intrauterine Growth Retardation." *European Journal of Clinical Nutrition* 57, no. 2 (February): 266–272. https://doi.org/10.1038/sj.ejcn.1601526.

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

Rose, Elaina. 1999. "Consumption Smoothing and Excess Female Mortality in Rural India." *The Review of Economics and Statistics* 81, no. 1 (February): 41–49. https://doi.org/10.1162/003465399767923809.

Sable, Marjorie R., and Deborah Schild Wilkinson. 2000. "Impact of Perceived Stress, Major Life Events and Pregnancy Attitudes on Low Birth Weight." *Family Planning Perspectives* 32 (6): 288–294. https://doi.org/10.2307/2648197.

Siddiqui, Tasneem, Mohammad Towheedul Islam, and Zohra Akhter. 2015. "National strategy on the management of disaster and climate induced internal displacement (NSMDCIID)." PreventionWeb. https://www.preventionweb.net/publication/national-strategy-management-disaster-and-climate-induced-internal-displacement.

Simeonova, Emilia. 2011. "Out of Sight, Out of Mind? Natural Disasters and Pregnancy Outcomes in the USA." *CESifo Economic Studies* 57, no. 3 (September): 403–431. https://doi.org/10.1093/cesifo/ifr005.

Skidmore, Mark, and Hideki Toya. 2002. "Do Natural Disasters Promote Long-Run Growth?" *Economic Inquiry* 40 (4): 664–687. https://doi.org/10.1093/ei/40.4.664.

Skoufias, Emmanuel, and Katja Vinha. 2012. "Climate Variability and Child Height in Rural Mexico." *Economics & Human Biology* 10, no. 1 (January 1, 2012): 54–73. https://doi.org/10.1016/j.ehb.2011.06.001.

Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge. 2015. "What Are We Weighting For?" *The Journal of Human Resources* 50 (2): 301–316.

Sy, Bocar, Corine Frischknecht, Hy Dao, David Consuegra, and Gregory Giuliani. 2019. "Flood Hazard Assessment and the Role of Citizen Science." *Journal of Flood Risk Management* 12, no. S2 (November): e12519. https://doi.org/10.1111/jfr3.12519.

Syverson, Ali. 2024. "Still standing: How USAID's disaster-resilient construction in Pakistan is keeping children in school amidst devastating floods." PreventionWeb, July 25, 2024. https://www.preventionweb.net/news/still-standing-how-usaids-disaster-resilient-construction-pakistan-keeping-children-school.

Takasaki, Yoshito. 2017. "Do Natural Disasters Decrease the Gender Gap in Schooling?" *World Development* 94 (June): 75–89. https://doi.org/10.1016/j.worlddev.2016.12.041.

Thai, Thuan Q., and Evangelos M. Falaris. 2014. "Child Schooling, Child Health, and Rainfall Shocks: Evidence from Rural Vietnam." *The Journal of Development Studies* 50, no. 7 (July): 1025–1037. https://doi.org/10.1080/00220388.2014.903247.

Thomas, Duncan, Kathleen Beegle, Elizabeth Frankenberg, Bondan Sikoki, John Strauss, and Graciela Teruel. 2004. "Education in a Crisis." *Journal of Development Economics,* New Research on Education in Developing Economies, 74, no. 1 (June): 53–85. https://doi.org/10.1016/j.jdeveco.2003.12.004.

Tian, Xinping, Jinquan Gong, and Zhe Zhai. 2022. "Natural Disasters and Human Capital Accumulation: Evidence from the 1976 Tangshan Earthquake." *Economics of Education Review* 90 (October 1, 2022): 102304. https://doi.org/10.1016/j.econedurev.2022.102304.

Todd, Petra E., and Kenneth I. Wolpin. 2003. "On the Specification and Estimation of the Production Function for Cognitive Achievement." *The Economic Journal* 113, no. 485 (February 1, 2003): F3–F33. https://doi.org/10.1111/1468-0297.00097.

———. 2006. "Assessing the Impact of a School Subsidy Program in Mexico: Using a Social Experiment to Validate a Dynamic Behavioral Model of Child Schooling and Fertility." *American Economic Review* 96, no. 5 (December): 1384–1417. https://doi.org/10.1257/aer.96.5.1384.

Torche, Florencia. 2011. "The Effect of Maternal Stress on Birth Outcomes: Exploiting a Natural Experiment." *Demography* 48, no. 4 (August): 1473–1491. https://doi.org/10.1007/s13524-011-0054-z.

UNICEF. 2010. "Multiple Indicator Cluster Survey (MICS)." https://www.unicef.org/statistics/index_24302.html.

———. 2021a. *COVID-19: Effects of School Closures on Foundational Skills and Promising Practices for Monitoring and Mitigating Learning Loss.* Innocenti Working Papers. May 19, 2021. https://doi.org/10.18356/25206796-2020-13.

———. 2021b. "The Impacts of Climate Change Put Almost Every Child at Risk," August 19, 2021. https://www.unicef.org/stories/impacts-climate-change-put-almost-every-child-risk.

United Nations. 2021. "Climate and Weather Related Disasters Surge Five-fold over 50 Years, but Early Warnings Save Lives." United Nations, September 1, 2021. UN News. https://news.un.org/en/story/2021/09/1098662.

Victora, Cesar G., Linda Adair, Caroline Fall, Pedro C. Hallal, Reynaldo Martorell, Linda Richter, and Harshpal Singh Sachdev. 2008. "Maternal and Child Undernutrition: Consequences for Adult Health and Human Capital." *The Lancet* 371, no. 9609 (January): 340–357. https://doi.org/10.1016/S0140-6736(07)61692-4.

Victora, Cesar Gomes, Mercedes de Onis, Pedro Curi Hallal, Monika Blössner, and Roger Shrimpton. 2010. "Worldwide Timing of Growth Faltering: Revisiting Implications for Interventions." *Pediatrics* 125, no. 3 (March): e473–e480. https://doi.org/10.1542/peds.2009-1519.

Wu, Jia, Jiada Lin, and Xiao Han. 2023. "Compensation for Girls in Early Childhood and Its Long-Run Impact: Family Investment Strategies under Rainfall Shocks." *Journal of Population Economics* 36, no. 3 (July): 1225–1268. https://doi.org/10.1007/s00148-022-00901-5.

ONLINE APPENDIX

Are Natural Disasters Disastrous for Education? Evidence from Seven Asian Countries

A MICS Data Appendix (Online)

In this appendix, we provide additional details on the sample and variables from the 6th round of the Multiple Indicator Cluster Survey (MICS), which is used in this paper.

A.1 Sample Restriction

We use the 6th round of MICS (MICS6) (UNICEF 2010) to study the effects of natural disasters on educational outcomes. MICS is a global multi-purpose survey program conducted by the United Nations Children's Fund (UNICEF). From the mid-1990s, MICS has conducted multiple rounds of surveys with multistage probability designs covering over 120 countries. The surveys are cross-sectional, and in each round, they apply nearly uniform data collection instructions and survey questions across the countries included in that round. The datasets in each country and round are representative at national and sub-national levels. The goal of MICS is to provide internationally comparable data on the situation of children and women, offering key micro-level insights on progress in human-capital development. Hence, they collect information on (1) the households, such as the family structure, assets and wealth, and sanitation; (2) all women and men aged 15 to 49 years and all children under 5 years of age in those households; and (3) one randomly selected child aged 5 to 17 in each household. All datasets are publicly available and can be downloaded from https://mics.unicef.org/surveys in .sav format.

We focus on MICS6 because it includes more detailed information on educational outcomes for children aged 5 to 17. Before MICS6, responses on child demographic characteristics, child labor participation, and child discipline were included in the household questionnaire. In MICS6, an additional questionnaire was fielded for the randomly selected child aged 5 to 17, and this new questionnaire includes interviewer-administered tests to assess child cognitive skills directly. In total, six questionnaires are included in MICS6: the Household Questionnaire, Water Quality Testing Questionnaire, Women's Questionnaire, Men's Questionnaire, Age 5–17 Child Questionnaire, and Under Five Child Questionnaire. This study uses information from the Household, Individual, and Age 5–17 Child questionnaires.

Among Asian countries covered by MICS6, we focus on low- and middle-income countries where surveys were taken before the COVID-19 pandemic. Our analysis includes countries from South Asia (Bangladesh (2019), Nepal (2019), Pakistan (2017–2019)), East and Southeast Asia (Mongolia (2018), Thailand (2019)), and Central Asia (Kyrgyz Republic (2018), Turkmenistan (2019)).

Our analysis includes countries facing high-stakes disaster risks. For example, Bangladesh is a densely populated and low-lying country with substantial exposure to cyclones, floods, and drought. The country is predicted to be affected by increasingly extreme climatic conditions in the next few decades (Intergovernmental Panel On Climate Change 2014). The Bangladesh government expects that "the greatest single impact of climate change might be on human migration/displacement," estimating that "by 2050 one in every 7 people in Bangladesh will be displaced by climate change" (Comprehensive Disaster Management Programme 2015).

A.2 Measures: Education

We use MICS6 data on children's educational outcomes, including enrollments, attainments, and foundational learning skills. We explain in this section the construction of these variables.

For the surveyed child, MICS6 records the highest level and grade (or year) of school (or any early childhood educational program) ever attended, the current school year grade, the grade attended in the last school year, and the grade completion status. In addition, MICS6 administers literacy and numeracy assessment tests for the child selected for the 5–17 Child Questionnaire, if the child is between 7 and 14 years of age. The tests are conducted at home and regardless of the child's school enrollment or attendance status.

A.2.1 Attainment and Enrollment Questions

The Household Questionnaire includes information that is complementary to what is included in the 5–17 Child Questionnaire. Jointly, the Household and 5–17 Child questionnaires provide responses to the following questions:

- CB4 (ED4): *Has (name) ever attended school or any early childhood education programme?*
- CB5 (ED5): *What is the highest level and grade or year of school (name) has ever attended?*
- CB6 (ED6): *Did (he/she) ever complete that (grade/year)?*
- CB7 (ED9): *At any time during the current school year did (name) attend school or any early childhood education programme?*
- CB8 (ED10): *During this current school year, which level and grade or year is (name) attending?*
- CB9 (ED15): *At any time during the previous school year did (name) attend school or any early childhood education programme?*
- CB10 (ED16): *During that previous school year, which level and grade or year did (name) attend?*

Questions starting with the "CB" prefix are from the 5–17 Child Questionnaire, while "ED" is the prefix for questions from the Household Questionnaire. We build enrollment and attainment variables based on responses to the "CB" questions but replace missing values with responses to the "ED" questions.

For enrollment questions, let *edu_everschool*, *edu_enrollasty*, and *edu_enrolthisy* denote dummy variables ("No" as 0 and "Yes" as 1) storing raw responses to the ever enrolled (CB4/ED4), enrolled last year (CB9/EB15), and enrolled this year (CB7/ED9) questions.

Responses to each grade-enrolled question usually include a variable recording the "level" of school and a variable recording the "grade" within that level of school. Different data files for countries (or regions) may store this piece of information differently. Since education systems differ across countries, we construct a comparable enrolled "years of education" (yoe) variable based on the "level" and "grade" jointly. Let *edu_yoe_highest*, *edu_yoe_lasty*, and *edu_yoe_thisy* denote the constructed years of education variables corresponding to the highest grade attended (CB5/ED5), grade attended last year (CB10/ED16), and grade attended this year (CB8/ED10). Additionally, let *edu_complete* denote the response to whether the highest grade attended was completed (CB6/ED6).

A.2.2 Enrollment Status and Paths

Responses and Skip Logic. If a child answered "No" or has a missing value for *edu_everschool*, by the skip-pattern design, there should be no responses for the *edu_enrollasty* and *edu_enrolthisy* variables. However, in our sample, there are a limited number of child responses for which this skip-pattern logic was not followed. Aggregating the over 18,020 children with "No" as a response to the *edu_everschool* question, as well as those with NA responses to the *edu_everschool* question, we count in the enumeration below subsets of children with different types of unexpected response patterns:

1. $n = 43$: *edu_everschool* $= 0$, *edu_enrollasty* $= 1$, *edu_enrolthisy* $= 1$.
2. $n = 4$: *edu_everschool* $= 0$, *edu_enrollasty* $= 1$, *edu_enrolthisy* $= 0$.
3. $n = 17$: *edu_everschool* $= 0$, *edu_enrollasty* $= 0$, and *edu_enrolthisy* $= 1$.
4. $n = 50$: *edu_everschool* $= 0$, *edu_enrollasty* $= 0$, and *edu_enrolthisy* $= 0$.
5. $n = 1$: *edu_everschool* $= 0$, *edu_enrollasty* $=$ NA, *edu_enrolthisy* $= 0$.
6. $n = 1$: *edu_everschool* $= 0$, *edu_enrollasty* $= 0$, *edu_enrolthisy* $=$ NA.
7. $n = 9$: *edu_everschool* $=$ NA, *edu_enrollasty* $= 1$, *edu_enrolthisy* $= 1$.
8. $n = 0$: *edu_everschool* $=$ NA, *edu_enrollasty* $= 1$, and *edu_enrolthisy* $= 0$.
9. $n = 2$: *edu_everschool* $=$ NA, *edu_enrollasty* $= 0$, and *edu_enrolthisy* $= 1$.
10. $n = 1$: *edu_everschool* $=$ NA, *edu_enrollasty* $= 0$, and *edu_enrolthisy* $= 0$.

Note that in case 4 above, while the responses are logical, given the skip-logic, the values for *edu_enrollasty* and *edu_enrolthisy* should be NA.

Constructing E_{ever}, E_{t-1}, and E_t enrollment variables. We set the ever-enrolled variable E_{ever} equal to *edu_everschool* when the correct skip-logic is followed. When answers have skip-logic inconsistencies, we let the recent enrollment status variables supersede the response to *edu_everschool*. Specifically, for the 75 children from the cases enumerated above who answered "Yes" for one or both of the *edu_enrollasty* and *edu_enrolthisy* variables but "No" or "NA" for *edu_everschool*, we set $E_{ever} = 1$. Additionally, we set the lagged enrollment status variable E_{t-1} equal to *edu_enrollasty* and replace the missing value with zero if $E_{ever} = 0$. We set the current enrollment status variable E_t equal to *edu_enrolthisy* and replace the missing value with zero if $E_{ever} = 0$.

Given our variable construction strategies, the tabulation of E_{ever}, E_{t-1}, and E_t among the 144,471 sample children is given as follows:

- $E_{ever} = 0$ for $n = 17,956$ children, $E_{ever} = NA$ for $n = 45$, and $E_{ever} = 1$ otherwise;
- $E_{t-1} = 0$ for $n = 37,095$ children, $E_{t-1} = NA$ for $n = 77$, and $E_{t-1} = 1$ otherwise;

- $E_t = 0$ for $n = 31,021$ children, $E_t = NA$ for $n = 61$, and $E_t = 1$ otherwise.

Given the enumeration above, the sample sizes for the E_{ever}, E_{t-1}, and E_t variables in Table 2 are $144,426$, $144,394$, and $144,410$, respectively.

Figure 1 present the distribution of E_t by age and country. Jointly considering E_t and E_{t-1}, Figure C.7 presents conditional enrollment status transition rates.

Sample Across Enrollment Paths. We categorize sample children along five enrollment paths by jointly considering a child's ever-enrolled status (E_{ever}), enrollment status in the last school year (E_{t-1}), and enrollment status in this school year (E_t):

Path A: Ever-enrolled, enrolled last year, and enrolled this year;
Path B: Ever-enrolled, enrolled last year, but did not enroll this year;
Path C: Ever-enrolled, not enrolled last year, but enrolled this year;
Path D: Ever-enrolled, not enrolled last year, and not enrolled this year;
Path E: Never enrolled.

There are 144,471 children in the whole sample. Among them, 104,196 children are on path A, 3,099 children are on path B, 9,178 children are on path C, 8,852 children are on path D, and 17,956 children are on path E. A small number of remaining children could not be classified due to missing responses to enrollment questions.

A.2.3 Grade and Attainment

Constructing G_{max}, G_{t-1}, and G_t Enrolled-Grade Variables. Along paths A and C, we set the current enrolled-grade variable G_t equal to *edu_yoe_thisy*. Along paths A and B, we set the lagged enrolled-grade variable G_{t-1} equal to *edu_yoe_lasty*. Along path D, we set the max.-enrolled-grade variable G_{max} equal to *edu_yoe_highest*.

We note that along paths A and C, it should be the case that *edu_yoe_thisy* is equal to *edu_yoe_highest*, and this is only true for 103,495 out of 104,196 children and 9,061 out of 9,178 children, respectively. Along path B, *edu_yoe_lasty* should be equal to *edu_yoe_highest*, and this is true for 2,451 out of 3,097 children. In cases where the recent and highest grade responses are inconsistent, our strategy lets the recent enrolled-grade variables supersede responses to *edu_yoe_highest*.

Constructing A_{max}, A_{t-1}, and A_t Attainment Variables. Building on G_t, G_{t-1}, and G_{max}, as well as *edu_complete*, we construct three variables for attainment: highest attainment by survey date A_{max}, attainment at the start of last year A_{t-1}, and attainment at the start of this school year A_t. Along each path, we enumerate below how these variables are constructed:

Path A: Ever-enrolled, enrolled last year, and enrolled this year:

- $A_{max} = G_t$ if *edu_complete* $= 1$, $A_{max} = (G_t - 1)$ otherwise;
- $A_{t-1} = G_{t-1} - 1$;
- $A_t = G_t - 1$;

Path B: Ever-enrolled, enrolled last year, but did not enroll this year:

- $A_{max} = G_{t-1}$ if *edu_complete* $= 1$, $A_{max} = (G_{t-1} - 1)$ otherwise;
- $A_{t-1} = G_{t-1} - 1$;
- $A_t = A_{max}$;

Path C: Ever-enrolled, not enrolled last year, but enrolled this year:

- A_{max} same as path A;
- $A_{t-1} = G_t - 1$;
- $A_t = G_t - 1$;

Path D: Ever-enrolled, not enrolled last year, and not enrolled this year:

- $A_{max} = G_{max}$ if *edu_complete* $= 1$, $A_{max} = (G_{max} - 1)$ otherwise;
- $A_{t-1} = A_{max}$;
- $A_t = A_{max}$;

Path E: Never enrolled:

- $A_{max} = 0$;
- $A_{t-1} = 0$;
- $A_t = 0$.

In the enumeration above, we use the following logic to construct A_{max}: for path A, A_{max} is the same as the grade this year (*edu_yoe_thisy*) if *edu_complete* is 1, and A_{max} is equal to *edu_yoe_thisy* minus 1 if *edu_complete* is not 1; for path B, A_{max} is calculated similarly as along path A, but we use the enrolled-grade last year (*edu_yoe_lasty*) instead of the enrolled-grade this year; path C is treated identically to path A; for path D, attainment is equal to *edu_yoe_highest* if *edu_complete* is 1 and equal to *edu_yoe_highest* minus 1 otherwise; and for path E, the highest attainment is zero.

We use the following logic to construct A_{t-1}: attainment at the start of the last school year, A_{t-1}, is the enrolled-grade last year minus 1 for paths A and B; for path C, since the child was not enrolled last year but is enrolled this year, we know that the attainment at the start of last year should be the enrolled-grade this year minus one; and children on paths D and E have $A_{t-1} = A_{max}$.

We use the following logic to construct A_t: attainment at the start of this school year A_t is the enrolled-grade last year minus 1 for path A; children on path B were enrolled last year but are not enrolled this year, so $A_t = A_{max}$; for path C, since the child was not enrolled last year but is enrolled this year, we know the attainment at the start of this year should be the enrolled-grade this year minus one; and children on paths D and E have $A_{t-1} = A_{max}$. Figure 2 presents averages of A_t by country and age, as well as gender and age.

A.2.4 MICS6 Test Scores

We use the foundational learning skills module in the MICS6 5–17 Child Questionnaire to construct test scores for reading and math. The surveyor, given respondent permission, administers the test to the selected child from the 5–17 Child Questionnaire, if the child is between 7 and 14 years of age.

As mentioned in the main text, in our sample, only about 60% of the eligible children have reading scores (see Appendix Figure C.3); hence, our analysis in the main text focuses on math scores, which are much more widely available (see Appendix Figure C.2). For completeness, we describe here how we constructed both reading and math scores.

Reading Skills. MICS administers a comparable story for the reading test across survey locations. The local MICS survey team customizes the story based on the language spoken at home and taught at school.[A.1] The reading test includes the following components:

Component (1): How many words from the story are read correctly?
Component (2): How well did the child read the story?
Component (3): Does the child comprehend the story?

For component (1), raw variable FL20B records the number of incorrectly read or missed words, and we construct the variable *read_score_wordcorrect* by counting the number of correctly read words. The story word count can differ due to language differences: for Mongolia, the story has 67 words, and the variable $read\_score\_wordcorrect = (67 - \text{FL20B})$; for Turkmenistan, $read\_score\_wordcorrect = (69 - \text{FL20B})$; and for other countries, the story has 72 words. Component (2) measures if at least one word is correct, if the child did not read any words correctly, and if the child did not try to read the story. We do not use component (2) since it duplicates information captured in component (1). Component (3) includes questions testing how well the child understands the story, and we construct the variable *read_score_comp* by counting the number of questions the child answered correctly. Finally, we generate the total reading score, *read_score_total*, by aggregating over *read_score_wordcorrect* and *read_score_comp*. Appendix Figure C.9 presents the distribution of *read_score_total*.

Math Skills. The MICS math test is uniform across countries and includes the following components:

Component (1): six symbol recognition questions (e.g., for the numbers 9, 12, etc.);
Component (2): five number comparison questions (e.g., between 7 and 5 or 65 and 67);
Component (3): five addition questions;
Component (4): five questions to identify the next number (e.g., given 20, X, 40, and 50, which number should X be).

For each question, surveys of most countries only record if it is answered correctly or not. We compute a total score for each component by giving a score of 1 if a question is answered correctly and a score of 0 if it is answered incorrectly or not attempted. We construct the variable *math_score_total* as the sum of the component-specific scores *math_score_sym*, *math_score_big*, *math_score_add*, and *math_score_next*. Figure 3 presents the distribution of *math_score_total*.

As exceptions, the surveys in the Kyrgyz Republic and Pakistan provide more response details. For example, for the number comparison question, the survey details what the child chooses as the larger number. As another example, the survey records the incorrect sums for the addition questions. For cross-country comparability, we do not consider these details in constructing the aggregate math score.

A.1. In Bangladesh, the story is in English or Bangla; in the Kyrgyz Republic, the story is in Kyrgyz, English, Russian, Uzbek, Tajik, Kazakh, Dungan, or Uygur; in Mongolia, the story is in Mongolian, Kazakh, or Tuva; in Nepal, the story is in Nepali, Bhojpuri, Maithili, or English; in Punjab, Pakistan, the story is in English or Urdu; in Sindh, Pakistan, the story is in English, Urdu, or Sindhi; in Balochistan, Pakistan, the story is in English, Urdu, Balochi, Brahivi, Pushto, Punjabi, or Dari/Farsi; in Khyber Pakhtunkhwa, Pakistan, the story is in English, Urdu, Pushto, Hindko, Siraiki, or Kohistani/Gujari; in Thailand, the story is in Thai or English; and in Turkmenistan, the story is in Turkmen, Uzbek, or Russian.

A.3 Measures: Child, Parental, and Household Attributes

Table C.2 present summary statistics on child age, child gender, parental education, and parent-child co-residency status by country. We describe the construction of these variables in this section.

A.3.1 Child Characteristics

The MICS survey is implemented at the household level and surveys individuals in the household, with a focus on women and children. If the child selected for the 5–17 Child Questionnaire is also the respondent for the Household Questionnaire, then demographic and educational information for the child is included in the Household Questionnaire. Otherwise, this information is collected in the 5–17 Child Questionnaire only. For each member of the surveyed household, MICS asks "is (name) is male or female" (question HL4 in the "hl" file), and our child gender variable is based on the answer to this question for the child selected for the 5 to 17 Child Questionnaire.

We construct a birth date variable based on the responses to the HL5 and CB2 questions from the "hl" files (5–17 Child Questionnaire) and "fs" files (Household Questionnaire). We construct the child age from the HL6 and CB3 questions. We obtain the child gender from the response to HL4.

A.3.2 Parents' Characteristics

We use "natural mother's line number in household" and "natural father's line number in household" to link observations in the Household and Child questionnaires. In both the "fs" and "hl" files, the "melevel" and "felevel" variables report maternal and paternal educational attainment. We use "melevel" from the "fs" file if data are available and otherwise use the information from the "hl" file. We use "felevel" from the "hl" file for the father's education. Appendix Figure C.4 presents the distributions of the shares of mothers who have ever been educated and with secondary schooling.

A.3.3 Parental Loss and Co-residency

MICS asks if one individual's mother or father is alive and if a living mother or father resides in the same household as the child or resides elsewhere. Based on this information, we construct indicators of the maternal, paternal, and joint parental loss status and parent-child co-residency status. Appendix Figure C.5 and Appendix Figure C.6 each present three plots by country and age. The former illustrates the shares of children experiencing parental loss, including maternal, paternal, and joint loss, while the latter shows the shares of children co-residing with parents, including mother-child and father-child co-residence.

A.4 Sample Weights in MICS

In this section, we discuss the use of weights for MICS analysis in our setting. The analysis in our main text does not use weights. In this section, we discuss the use of weights in our empirical context and we provide weighted summary statistics tables.

A.4.1 Weights, missing weights, and alternative weighting schemes

"Weighting" in empirical research refers to assigning different importance values to observations in order to improve representativeness of population level statistics. In this study, our primary focus is on the estimation of causal effects. As Solon, Haider, and Wooldridge (2015) note, the use of sampling weights can reduce the efficiency of estimates, and their application is not always warranted. Following Solon, Haider, and Wooldridge (2015), we report heteroskedasticity-robust standard errors and present our main causal effect estimates without applying sampling weights.

Another reason we do not rely primarily on the weighted results is that some individuals in the MICS data are assigned a sample weight of zero, for reasons that are not documented. The MICS surveys provide sampling weights at various levels—households, women aged 15–49, men aged 15–29, children under age 5, and children aged 5–17, among others.[A.2] Specifically, MICS6 provides *fsweight* as the sampling weight for children aged 5–17. However, in our sample, 3,683 out of 144,471 children are assigned *fsweight* of 0. Of these observations, 1,231 are from Bangladesh, 8 from the Kyrgyz Republic, 191 from Mongolia, 34 from Nepal, 2,043 from Pakistan, 131 from Thailand, and 45 from Turkmenistan. Among the non-zero weights, weight values range from approximately 0.005 to 52.53. We also found that individuals with zero and with non-zero weights have similar individual and parental characteristics distributions. A higher share of individuals with zero weights is from the Pakistan sample, and there are small but significant differences in exposures to disasters for individuals with zero and non-zero weights. Overall, we did not find patterns in the data that would justify the exclusion of the zero weight subsample from our analysis.

Furthermore, it is challenging to use the *fsweight* variable appropriately for MICS in a multi-country setting. The *fsweight* variable provides relative weights for sample points within a country. In our multi-country setting, weights should capture relative child population sizes across countries. We collected data on the population of children aged 5–19 for the sample countries from https://www.populationpyramid.net/ to match the MICS survey region, time, and age range. Our measures (column 3 in Table C.13) correlate with the sum of MICS weights (column 6 of Table C.13) for each survey region. This indicates that MICS weights do attempt to take cross-country population sizes into account, although we did not find clear documentation on how this is done. It is plausible that the MICS cross-country weights are computed using undocumented, survey-specific procedures and therefore better capture cross-country representativeness. To check robustness, we developed two alternative weighting schemes.

We present summary statistics using the alternative weighting schemes in this appendix.[A.3] Under the first weighting scheme, we capture within-country relative sample weights using MICS weights and cross-country relative sample weights using our separately collected child population sizes information (column 3 in Table C.13). Tables C.14 and C.15 present summary statistics using this weighting scheme. In the second weighting scheme, we only use the MICS weights as provided for both within-country and cross-country representativeness.

A.2. MICS surveys are sometimes nationally representative and sometimes representative only for specific population groups within a country. See https://mics.unicef.org/faq for more details. Documentation on sample-weight construction is available in "Sampling and Mapping" at https://mics.unicef.org/tools.

A.3. More analysis results with sampling weights applied are presented in project repository: https://github.com/ClimateInequality/PrjRDSEpub

Tables C.16 and C.17 present the summary statistics using this weighting scheme.

A.4.2 Summary statistics with weights

Observations with *fsweight* equal to zero are excluded from the analysis, resulting in a maximum sample size of approximately 140,000 children in all the summary statistics tables with sample weights applied. Comparing Tables C.14 and C.16 with Table 2, we find that weighted and unweighted moments of key outcome variables and covariates are very similar. A comparison of Tables C.15 and C.17 with Table 4 indicates that applying sampling weights results in broadly similar disaster-exposure statistics. For example, among outcome variables, the "enrollment in this school year t" variable has an average of 0.79 in our unweighted results, and values of 0.80 and 0.76 using our two alternative weighting schemes. Among disaster-exposure variables, the average "number of months with any disasters in the first 1000 days" has values of 3.05, and values of 3.26 and 2.84 under the two weighting schemes. Among covariates, the average "age of child" is 10.49, and 10.57 and 10.59 under the two weighting schemes.

B EM-DAT Appendix (Online)

B.1 EM-DAT Dataset

We use EM-DAT (1900–2023) to construct natural disaster exposure variables. It is an international database compiled by the Centre for Research on the Epidemiology of Disaster (CRED) (Delforge et al. 2023). It records the occurrence and impacts of over 21,000 disasters worldwide from 1900 to the present. The database categorizes all events into natural and technological disasters. Natural disasters are further divided into five subgroups: geophysical, meteorological, hydrological, climatological, and biological disasters. Technological disasters include industrial accidents, transport accidents, and other miscellaneous accidents. Our study exclusively considers events classified as natural disasters in EM-DAT.

The dataset is publicly available and can be downloaded from https://public.emdat.be/. Disaster types, countries, and time periods of occurrences can be used as filters to download disaster files for certain types of events and specific areas. The downloaded raw file lists each disaster in a distinct row, with columns detailing the characteristics and associated information of each event.

The coding of disasters is internationally standardized, facilitating linkages to other databases. Each disaster has a unique identifier that combines the year, sequence number, and three-letter country code (alpha-3 code). For example, "2016-0375-PAK" identifies a flash flood that occurred in Pakistan in 2016. Disasters affecting multiple countries share the same year and sequence number but have different country suffixes, and they are recorded separately for each country.

B.2 Context and Impact Variables

The information associated with each disaster can be categorized into context and impact variables. The geographical and temporal information of each disaster are considered as context variables. Impact variables measure the human and economic impacts of the events.

B.2.1 Context Variables and Linking to MICS

The geographical information includes variables for the country, region, continent, and river basin where the disaster took place, and also includes coordinates for the epicenters of earthquakes. Crucially, EM-DAT reports the administrative levels and names of locations affected by each disaster. This project relies on this information to link disaster locations and locations where MICS6 children reside.

The temporal information includes variables for the start and end dates of each disaster. We use this temporal information to match the timing of disasters to the life-cycle of each child. Specifically, given location information and by combining birth dates, survey dates, and disaster starts and durations, we generate a child-level monthly panel dataset that records for each child at each age-in-months whether a disaster occurred and the characteristics of the disaster.

B.2.2 Impact Variables and Disaster Severity Classification

Impact variables enable us to assess the severity of each disaster. EM-DAT includes statistics on deaths, missing persons, injuries, affected individuals, and those rendered homeless due to each disaster. Some EM-DAT entries also include economic impact information in terms of the total estimated damages, reconstruction cost, and insured losses associated with that event.

We jointly use the number of dead and injured, as well as the number of individuals affected, to classify the severity of disasters. We do not use economic damage variables in classifying disasters due to the relatively limited availability of those variables.

B.3 Linking Details and Illustrative Examples

EM-DAT provides information on disaster-affected areas at both administrative level 1 and level 2 through several variables: "GeoLocations", "Location", and "AdmLevel". "GeoLocations" and "Location" are largely similar, each listing the names of affected areas. The difference is that "GeoLocations" is the cleaned and standardized version of "Location", generated by the EM-DAT team as part of their ongoing effort to harmonize location names and assign administrative-level codes. The original "Location" variable captures place names as reported by sources such as UN agencies, NGOs, insurance companies, and research institutions, while "GeoLocations" enhances this information by indicating whether the location corresponds to administrative level 1 or 2. The "AdmLevel" variable complements this by specifying the administrative level using values such as 1, 2, or "1;2". For instance, an earthquake that happened in 2000 in Bangladesh (disaster ID: "2000-0023-BGD") lists "Maheshkhali area (Cox's Bazar district, Chittagong province)" under "Location" variable, while "GeoLocations" identifies it more precisely as "Cox's Bazar (Adm2)", with "AdmLevel" coded as 2.

However, This harmonization effort has primarily focused on disaster events from 2000 onward and remains in progress at the time of writing. Not all disaster records contain "GeoLocations". When available, we use "GeoLocations" to match disaster locations to the administrative areas where MICS6 children reside. For records lacking this variable, we match using "Location" by manually searching across administrative level names.[B.1] Of the 355 disaster events in our dataset, 43 lack information in the "GeoLocations" variable, and only 12 are missing location details in both "GeoLocations" and "Location". For these cases, we assign disaster exposure at the country level by matching the disaster to all subnational areas within the country.[B.2]

We extract and clean the affected location names for each disaster and store them in a variable called "locname". The cleaning process involves three main steps: First, remove redundant strings such as "District", "district", "(Administrative unit not available)", "Administrative unit not available", "Agency", "agency", "regions", "region", "Regions", "Region", "(Adm1)", "(Adm1)", etc. which are not useful for matching. Second, split location names

B.1. EM-DAT provides additional documentation on the construction of these location variables at https://doc.emdat.be/docs/introduction/.

B.2. Most of these events are floods or epidemics in Bangladesh and Nepal. Epidemics typically involve widespread exposure and transmission risk; thus, for any-disaster measures, we assume nationwide exposure. For the severe-disaster measure, only four events fall under this type of matching.

separated by commas into individual entries. Third, match cleaned location names to the corresponding administrative units based on the "AdmLevel" variable, which indicates whether the affected areas are at level 1, level 2, or both. For this step, we construct a boundary linkage file that contains harmonized location names at the regional, administrative level 1, and administrative level 2 for each country. To generate the boundary linkage file, we use boundary files from United Nations OCHA Regional Office for Asia and the Pacific (ROAP).[B.3] We obtain the location names at regional level[B.4] , then administrative level 1, and level administrative level 2 for each country, and pool them in a boundary-linkage file linking all three levels. Each disaster-location is then matched to the corresponding geographic units in the MICS6 survey. The matching is conditional on the administrative level specified in the "AdmLevel" variable. For example, if "AdmLevel" is 2, we only attempt matches at the second administrative level; if it is 1, we match at the first level; and if "AdmLevel" is missing, we search across all levels.

We illustrate this with two examples. The flash-flood disaster "2016-0375-PAK" resulted from heavy rain in Pakistan. From the date variables, we know that this flood started on 5 August 2016 and ended on 8 August 2016. The four-day disaster led to 32 deaths and left 2,900 individuals homeless. The disaster took place in "Balochistan, Sindh provinces," according to the "Location" variable. Additionally, the "GeoLocations" variable, which is derived from the "Location" variable, reports "Balochistan, Sindh (Adm1)." This disaster is then matched with all districts in the provinces. In the case of the 2017 landslide in Bangladesh ("2017-0174-BGD"), which occurred in June and caused 347 deaths and affected 80,187 people, the "Location" variable lists: "Chittagong (Teknaf, Rangunia, Chandanaish), Rangamati, Bandarban, Cox's Bazar, Khagrachari". The "GeoLocations" variable provides harmonized administrative level 2 locations: "Bandarban, Chittagong, Cox's Bazar, Khagrachhari, Rangamati (Adm2)". These names are then matched to the corresponding districts in the MICS6 data.

All project data processing, integration, and analysis code are shared at our project repository: https://github.com/ClimateInequality/PrjRDSEpub.

B.3. Access to the boundary files on OCHA ROAP: https://data.humdata.org/organization/ocha-roap.
For Bangladesh, we use https://data.humdata.org/dataset/cod-ab-bgd.
For Mongolia, we use https://data.humdata.org/dataset/cod-ab-mng.
For Nepal, we use https://data.humdata.org/dataset/cod-ab-npl.
For Pakistan, we use https://data.humdata.org/dataset/cod-ab-pak.
For Thailand, we use https://data.humdata.org/dataset/cod-ab-tha.
For Kyrgyz Republic, we use https://data.humdata.org/dataset/cod-ab-kgz.
For Turkmenistan, we use https://data.humdata.org/dataset/geoboundaries-admin-boundaries-for-turkmenistan?.

B.4. For Mongolia, we observe which region children are living in and one region can contain several divisions at administrative level 1, which are provinces.

C Additional Figures and Tables (Online)

This Appendix section provides additional tables and figures. We present additional summary statistics on children and parental characteristics, as well as disaster exposures in Tables C.1, C.2, and C.4. Table C.3 presents the natural-disaster characteristics by event categories. Table C.5 presents migratory-history summary statistics for the mothers of the children. Figures C.2 and C.3 present the shares of the sample reporting math and reading test scores, respectively. Figures C.4, C.5, and C.6 plot parental and household characteristics. Figure C.7 shows the enrollment status of children in the survey year, conditional on whether they were enrolled in the previous year. The distributions of grade progression and reading test scores are presented in Figures C.8 and C.9, respectively.

This section also includes supplementary regression results. Table C.6 shows results with fewer controls for the effects of "all disasters" on enrollments. Table C.7 shows results for the effects of disaster exposures on enrollments with various disaster-exposure measures. For the math-score outcome, Table C.8 shows results using different measures for disaster exposures. Table C.9 and Table C.10 present heterogeneity analyses for the effects of disaster exposures on enrollments and math scores by age, respectively. Table C.11 and Table C.12 present results for the effects of disaster exposures on enrollments and math scores for children of non-migrant mothers, respectively.

Table C.13 reports the values used to construct the sampling weight variables for different samples. Tables C.14 and C.15 present the summary statistics for children applying the sampling weights variable using *fsweight* modified by population size in each region and year. Tables C.16 and C.17 present the summary statistics for children applying the -weights variable *fsweight* directly.

Table C.1: Summary statistics for educational outcomes by country

	Mean	SD	Min	Max	N
Bangladesh					
Enrollment in this school year t	0.85	0.36	0	1	40,617
Enrollment in last school year t-1	0.79	0.41	0	1	40,616
Attainment (highest)	3.91	3.20	0	14	40,614
Math score	16.32	5.87	0	21	22,354
Kyrgyz Republic					
Enrollment in this school year t	0.93	0.25	0	1	3,897
Enrollment in last school year t-1	0.90	0.30	0	1	3,897
Attainment (highest)	3.91	3.38	0	13	3,897
Math score	19.40	2.70	0	21	2,349
Mongolia					
Enrollment in this school year t	0.94	0.24	0	1	7,627
Enrollment in last school year t-1	0.94	0.24	0	1	7,627
Attainment (highest)	4.14	3.50	0	16	7,627
Math score	19.31	3.38	0	21	4,546
Nepal					
Enrollment in this school year t	0.91	0.29	0	1	7,823
Enrollment in last school year t-1	0.90	0.31	0	1	7,823
Attainment (highest)	3.94	3.38	0	12	7,821
Math score	15.96	6.49	0	21	4,617
Pakistan					
Enrollment in this school year t	0.68	0.47	0	1	71,064
Enrollment in last school year t-1	0.63	0.48	0	1	71,050
Attainment (highest)	2.77	3.37	0	13	71,027
Math score (total)	10.09	7.43	0	21	36,006
Thailand					
Enrollment in this school year t	0.98	0.13	0	1	9,607
Enrollment in last school year t-1	0.98	0.15	0	1	9,606
Attainment (highest)	2.78	2.60	0	9	9,597
Math score	19.57	3.27	0	21	6,704
Turkmenistan					
Enrollment in this school year t	0.91	0.29	0	1	3,775
Enrollment in last school year t-1	0.87	0.34	0	1	3,775
Attainment (highest)	4.02	3.35	0	12	3,775
Math score	20.11	1.97	0	21	2,128

Note: This table shows summary statistics for key educational outcome variables by country. Our sample is dominated by children from Bangladesh and Pakistan. This table includes the enrollment status for the current and last school years. The attainment (highest) is defined as completed grades of schooling. In Thailand, only children up to age 14 are surveyed.

Table C.2: Summary statistics for child and parent attributes by country

	Mean	SD	N
Bangladesh			
Age of child	10.95	3.72	40,617
Female	0.48	0.50	40,617
Mother ever educated	0.74	0.44	40,587
Mother has secondary sch. education	0.46	0.50	40,587
Mother is living in same HH	0.92	0.27	40,603
Father is living in same HH	0.83	0.38	40,581
Kyrgyz Republic			
Age of child	10.34	3.67	3,897
Female	0.47	0.50	3,897
Mother ever educated	0.99	0.09	3,897
Mother has secondary sch. education	0.92	0.27	3,897
Mother is living in same HH	0.85	0.36	3,888
Father is living in same HH	0.75	0.43	3,879
Mongolia			
Age of child	10.06	3.67	7,628
Female	0.49	0.50	7,628
Mother ever educated	0.94	0.25	7,595
Mother has secondary sch. education	0.64	0.48	7,595
Mother is living in same HH	0.87	0.34	7,622
Father is living in same HH	0.74	0.44	7,529
Nepal			
Age of child	10.55	3.80	7,824
Female	0.50	0.50	7,824
Mother ever educated	0.52	0.50	7,821
Mother has secondary sch. education	0.24	0.43	7,821
Mother is living in same HH	0.91	0.29	7,821
Father is living in same HH	0.67	0.47	7,814
Pakistan			
Age of child	10.49	3.87	71,121
Female	0.48	0.50	71,121
Mother ever educated	0.36	0.48	71,059
Mother has secondary sch. education	0.16	0.36	71,059
Mother is living in same HH	0.95	0.22	70,945
Father is living in same HH	0.86	0.35	71,020
Thailand			
Age of child	9.03	2.91	9,608
Female	0.48	0.50	9,608
Mother ever educated	0.95	0.21	9,603
Mother has secondary sch. education	0.36	0.48	9,603
Mother is living in same HH	0.69	0.46	9,573
Father is living in same HH	0.56	0.50	9,482
Turkmenistan			
Age of child	10.08	3.81	3,776
Female	0.48	0.50	3,776
Mother ever educated	1	0.02	3,776
Mother has secondary sch. education	0.25	0.43	3,776
Mother is living in same HH	0.95	0.22	3,770
Father is living in same HH	0.86	0.35	3,763

Note: This table shows summary statistics for some demographic characteristics by country. For example, in Bangladesh, the average age of children is about 11 years; 48% of the children in our sample are female.

Table C.3: Natural disaster characteristics by event categories

Disasters	# of Events	Mean	SD	Min	1st quartile	2nd quartile	3st quartile	Max
Flood	**155**							
Casualties	44	920	3,174	11	55	190	479	20,671
Affected	134	1,308,461	4,045,562	3	3,133	75,000	612,978	36,000,000
Storm	**102**							
Casualties	45	1,798	8,879	16	84	154	320	59,516
Affected	84	342,078	1,168,749	6	500	4,525	57,041	8,978,541
Extreme temperature	**33**							
Casualties	7	1,078	1,676	12	161	306	1,180	4,550
Affected	20	181,107	324,294	24	1,750	50,000	114,250	1,000,000
Earthquake	**22**							
Casualties	16	13,933	50,228	17	66	100	614	201,647
Affected	20	347,199	1,147,602	16	186	8,074	69,085	5,128,309
Epidemic	**22**							
Casualties	2	28,223	36,354	2,517	15,370	28,223	41,076	53,929
Affected	20	25,116	54,298	4	116	1,686	40,384	236,558
Landslide	**11**							
Casualties	5	119	141	18	28	34	166	347
Affected	7	27,829	30,394	5	4,181	18,016	44,115	80,187
Drought	**8**							
Affected	3	7,721,171	3,813,503	4,680,912	5,581,757	6,482,602	9,241,301	12,000,000
Wildfire	**2**							
Affected	1	4,000						

Note: This table shows characteristics of all the natural disaster events linked to within-country locations from 1999 to 2019. There are in total 355 disasters. Variable “Casualties” refers to the sum of number of total deaths and injured (if both information is recorded for one disaster), and variable “Affected” refers to the number of total affected. We present the distribution of human impacts from disasters by disaster types.

Table C.4: Summary statistics for disaster exposure by country

	Mean	SD	Min	Max	N
Bangladesh					
Had any disaster					
in most recent 12 mo.	0.73	0.45	0	1	40,617
in year prior to 12 mo. ago	0.71	0.45	0	1	40,617
# of mo. with any disaster					
in mid-child life	6.98	7.30	0	41	40,617
in the first 1,000 days (early life)	3.97	3.62	0	18	40,617
Kyrgyz Republic					
Had any disaster					
in most recent 12 mo.	0	0	0	0	3,897
in year prior to 12 mo. ago	0	0	0	0	3,897
# of mo. with any disaster					
in mid-child life	2.54	2.70	0	13	3,897
in the first 1,000 days (early life)	1.19	1.51	0	5	3,897
Mongolia					
Had any disaster					
in most recent 12 mo.	0.86	0.35	0	1	7,628
in year prior to 12 mo. ago	0.86	0.35	0	1	7,628
# of mo. with any disaster					
in mid-child life	6.75	5.41	0	21	7,628
in the first 1,000 days (early life)	2.74	3.18	0	10	7,628
Nepal					
Had any disaster					
in most recent 12 mo.	0.19	0.39	0	1	7,824
in year prior to 12 mo. ago	0.54	0.50	0	1	7,824
# of mo. with any disaster					
in mid-child life	5.47	5.61	0	13	7,824
in the first 1,000 days (early life)	2.37	4.10	0	13	7,824
Pakistan					
Had any disaster					
in most recent 12 mo.	0.62	0.49	0	1	71,121
in year prior to 12 mo. ago	0.65	0.48	0	1	71,121
# of mo. with any disaster					
in mid-child life	6.60	6.59	0	29	71,121
in the first 1,000 days (early life)	2.58	3.25	0	13	71,121
Thailand					
Had any disaster					
in most recent 12 mo.	0.06	0.24	0	1	9,608
in year prior to 12 mo. ago	0.49	0.50	0	1	9,608
# of mo. with any disaster					
in mid-child life	27.40	13.91	0	60	9,608
in the first 1,000 days (early life)	5.34	6.09	0	24	9,608

Note: This table shows summary statistics for location-specific or child-and-location-specific disaster experience indicators by country. The column "Mean" shows the share of children who have experienced any type of disaster shock in each period. *Had any disaster* is denoted as DB^p in the equations—an indicator equal to one if there is any type of disaster in the designated time span and zero if not. There is huge variation across countries, and Turkmenistan is excluded here because there was no natural disaster recorded in EM-DAT in the time span we are investigating (1999–2019). The mid-child life is defined as the period between the first 1,000 days and two years prior to the survey month. In Thailand, only children up to age 14 are surveyed. Turkmenistan is not listed here because there are no disasters recorded for Turkmenistan during the spans of time we are considering.

Table C.5: Summary statistics for residential duration by country

	Percentiles				Mean	SD	Obs
	5th	10th	15th	20th			
Bangladesh							
Residential duration exceeds age	0	0	1	1	0.89	0.32	33,674
Ratio of residential duration to age	0.43	0.88	1	1	0.94	0.19	33,674
Kyrgyz Republic							
Residential duration exceeds age	0	0	1	1	0.86	0.35	2,926
Ratio of residential duration to age	0.36	0.71	1	1	0.93	0.21	2,926
Mongolia							
Residential duration exceeds age	0	0	0	1	0.83	0.38	5,883
Ratio of residential duration to age	0.38	0.67	0.88	1	0.92	0.20	5,883
Nepal							
Residential duration exceeds age	0	0	0	1	0.85	0.36	6,401
Ratio of residential duration to age	0.35	0.67	0.94	1	0.93	0.21	6,401
Pakistan							
Residential duration exceeds age	0	0	1	1	0.89	0.32	40,143
Ratio of residential duration to age	0.33	0.83	1	1	0.93	0.21	40,143
Thailand							
Residential duration exceeds age	0	0	1	1	0.86	0.35	6,157
Ratio of residential duration to age	0.38	0.73	1	1	0.93	0.20	6,157
Turkmenistan							
Residential duration exceeds age	1	1	1	1	0.96	0.20	3,335
Ratio of residential duration to age	1	1	1	1	0.98	0.11	3,335

Note: This table shows summary statistics for the migratory history of mothers of children selected for the 5–17 Child Questionnaire. "Residential duration exceeds age" is a binary variable equal to 1 if a mother has been living in the current location since the approximate conception month of the child. "Ratio of residential duration to age" denotes the fraction of a child's life during which the mother has lived in the same location—if the child is 10 years old, and the mother has been living in the current location for 7 years, then this number is calculated as 0.7.

Table C.6: Effects of disasters on enrollments

	(1)	(2)	(3)
Had disaster in most recent 12 mo.	-0.003	-0.002	-0.004
	(0.006)	(0.006)	(0.006)
# of mo. with disaster in the first 1,000 days	-0.002^{***}	-0.002^{***}	-0.001^{**}
	(0.000)	(0.000)	(0.000)
Enrollment in year $t-1$	0.648^{***}	0.641^{***}	0.388^{***}
	(0.010)	(0.010)	(0.012)
Attainment at start of t	0.025^{***}	0.024^{***}	0.012^{***}
	(0.001)	(0.001)	(0.002)
Female		-0.015^{***}	-0.006^{***}
		(0.002)	(0.002)
Mother is alive		-0.015^{**}	-0.009
		(0.006)	(0.006)
Father is alive		0.013^{***}	0.012^{***}
		(0.004)	(0.004)
Mother is alive × living in same HH		0.029^{***}	0.025^{***}
		(0.005)	(0.005)
Father is alive × living in same HH		-0.005^{**}	-0.005^{**}
		(0.002)	(0.002)
Mother ever educated		0.037^{***}	0.041^{***}
		(0.003)	(0.003)
Mother ever educated × has secondary education		0.004^{**}	0.011^{***}
		(0.002)	(0.002)
Observations	144354	143645	143645
Within-country location FE	Y	Y	Y
Interview year FE	Y	Y	Y
Interview month FE	Y	Y	Y
Child age FE	Y	Y	Y
Enrollment $t-1$ × age group FE			Y
Attainment t × age group FE			Y
Enrollment $t-1$ × country FE			Y
Attainment t × country FE			Y

Note: This table shows regression results corresponding to Eq. (2). The first 1,000 days is defined as the period from conception to 24 months of age in child development; hence, in total, there are 33 months in the period. The average number of months with a disaster in the first 1,000 days is about 3 months. About 57% of children in the whole sample have experienced a natural disaster in the most recent 12 months. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table C.7: Effects of disasters on enrollments using different disaster measures

	(1)	(2)	(3)
	Had disaster in		# of mo. with disaster in
	survey mo.	most recent 3 mo.	most recent 12 mo.
Recent disaster experience	0.006	0.003	0.003
	(0.005)	(0.005)	(0.003)
# of mo. with disaster in the first 1,000 days	-0.001^{**}	-0.001^{**}	-0.001^{**}
	(0.000)	(0.000)	(0.000)
Observations	143645	143645	143645

Note: This table shows regression results of Eq. (2) using different measures for recent shocks. We consider a binary indicator of any type of disaster that happened in the survey month (column 1), in the most recent 3 months (column 2), and in the most recent year (column 3). Then, we use the number of months when there was any type of natural disaster in the most recent year (column 4). Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table C.8: Effects of disasters on math scores using different disaster measures

	(1)	(2)	(3)
Had disaster in most recent 12 mo.	−0.052	0.055	
	(0.171)	(0.188)	
Had disaster in yr. prior 12 mo. ago	0.004		
	(0.164)		
Had disaster in mid-child life	−0.245		
	(0.167)		
Had disaster in the first 1,000 days	−0.284***		
	(0.109)		
# of mo. with disaster in recent 12 mo.			−0.061
			(0.119)
# of mo. with disaster in yr. prior 12 mo. ago		0.184	0.164
		(0.146)	(0.135)
# of mo. with disaster in mid-child life		−0.022	−0.022
		(0.017)	(0.017)
# of mo. with disaster in the first 1,000 days		−0.029**	−0.030**
		(0.015)	(0.015)
Observations	78305	78305	78305

Note: This table shows regression results of Eq. (3) using different measures for disaster shocks. In each column, four shocks covering one child's disaster exposure history are included, representing four time spans: the first 1,000 days, mid-child life (time between the first 1,000 days and most recent 2 years), 1 year prior to 12 months ago compared to the survey month, and the most recent year. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table C.9: Disasters and enrollments, heterogeneity across age groups

	(1) All disasters	(2) Flood	(3) Severe disasters	(4) Severe flood
Had disaster in most recent 12 mo.				
× Age 5–8	0.008	−0.019**	0.019*	0.045***
	(0.010)	(0.009)	(0.011)	(0.008)
× Age 9–12	−0.009	−0.014**	−0.004	−0.017***
	(0.006)	(0.007)	(0.008)	(0.006)
× Age 13–17	−0.012	−0.003	−0.008	−0.025***
	(0.009)	(0.009)	(0.010)	(0.008)
# of mo. with disaster in the first 1,000 days				
× Age 5–8	0.001	−0.001	−0.001	−0.005*
	(0.001)	(0.003)	(0.001)	(0.003)
× Age 9–12	−0.002***	−0.003***	−0.002***	−0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
× Age 13–17	−0.001	−0.002***	−0.003***	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	143,645	143,645	143,645	143,645

Note: This table shows heterogeneity analysis across ages for disaster effects on enrollment corresponding to Eq. (2) by interacting disaster shocks with age groups. For children aged 5–8, about 55% of them have experienced a natural disaster in the most recent 12 months, while 56% and 59% of children aged 9–12 and aged 13–17 had a disaster shock in this time span, respectively. The average number of months with a disaster in the first 1,000 days for children aged 5–8, 9–12, and 13–17 is about 2 months, 3 months, and 4 months, respectively. For the disaster intensity type, we consider all disasters, only floods, severe disasters (defined as causing more than 500 casualties or affecting at least 5,000 people), and only severe floods. Having various disaster intensity types provides the possibility for robustness checks on disaster experience construction. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table C.10: Disasters and math scores, heterogeneity across age groups

	(1) All disasters	(2) Flood	(3) Severe disasters	(4) Severe flood
# of mo. with disaster in mid-child life				
× Age 7–9	−0.020	0.016	−0.006	0.069
	(0.025)	(0.050)	(0.039)	(0.061)
× Age 10–12	−0.015	−0.034	−0.019	0.021
	(0.023)	(0.042)	(0.026)	(0.051)
× Age 13–14	−0.017	−0.030	−0.026	0.023
	(0.022)	(0.036)	(0.026)	(0.047)
# of mo. with disaster in the first 1,000 days				
× Age 7–9	−0.038*	−0.087	−0.031	−0.052
	(0.022)	(0.053)	(0.029)	(0.059)
× Age 10–12	0.014	−0.001	0.016	−0.002
	(0.017)	(0.027)	(0.024)	(0.041)
× Age 13–14	−0.030	−0.023	−0.028	−0.040
	(0.022)	(0.031)	(0.030)	(0.040)
Observations	78,303	78,303	78,303	78,303

Note: This table shows heterogeneity analysis across ages for disaster effects on math-test scores. This corresponds to Eq. (3), with interactions between disaster shocks and age groups. The first 1,000 days is defined as the period from conception to 24 months of age in child development; hence, in total, there are 33 months in the period. The mid-child life is defined as the period between the first 1,000 days and two years prior to the survey month. The average number of months covered in mid-child life is 53 months, 90 months, and 120 months for children aged 7–9, 10–12, and 13–14, respectively. For children in each age group, about 56% of them have experienced a natural disaster in the most recent 12 months. The average number of months with a disaster in the first 1,000 days for children aged 7–9, 10–12, and 13–14 is about 2 months, 3 months, and 4 months, respectively. The average number of months with a disaster in mid-child life is about 5.4 months, 8 months, and 10.5 months for children aged 7–9, 10–12, and 13–14, respectively. The average math-test score for children aged 7 to 9 is 12.3, with a standard deviation of 7.6. The average math-test score for children aged 9 to 12 is 15.2, and the standard deviation is 7. For the oldest group of children, aged 13 to 14, the average math-test score is 15.9, with a standard deviation of 6.9. The distribution of math-test scores across ages and countries is shown in Figure 3. For the disaster intensity type, we consider all disasters, only floods, severe disasters (defined as causing more than 500 casualties or affecting at least 5,000 people), and only severe floods. Having various disaster intensity types provides the possibility for robustness checks on disaster experience construction. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table C.11: Effects of disasters on enrollments for children of local non-mover mothers

	All disasters			Floods	Severe disasters	Severe floods
	(1)	(2)	(3)	(4)	(5)	(6)
Had disaster in recent 12 mo.	0.000	0.002	-0.001	-0.009^{**}	0.003	-0.006
	(0.005)	(0.006)	(0.005)	(0.004)	(0.009)	(0.006)
# of mo. with disaster in the first 1000 days	-0.002^{***}	-0.002^{***}	0.000	-0.002^{*}	-0.002^{**}	-0.003^{***}
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Observations	86,703	86,570	86,570	86,570	86,570	86,570
Within-country location FE	Y	Y	Y	Y	Y	Y
Interview year FE	Y	Y	Y	Y	Y	Y
Interview month FE	Y	Y	Y	Y	Y	Y
Child age FE	Y	Y	Y	Y	Y	Y
Enrollment $t-1$ × age group FE			Y	Y	Y	Y
Attainment t × age group FE			Y	Y	Y	Y
Enrollment $t-1$ × country FE			Y	Y	Y	Y
Attainment t × country FE			Y	Y	Y	Y

Note: This table shows regression results of Eq. (2) using a subsample of children whose mothers' duration of residence information is available and whose duration of residence in the current city, town or village of residence exceeds the child's age. See discussions in Section 2.3.3 Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table C.12: Effects of disasters on math scores for children of non-migrant mothers

	(1) All disasters	(2) Floods	(3) Severe disasters	(4) Severe floods
***Recent** experience: had disaster*				
in recent 12 mo.	−0.024	−0.352	−0.146	−0.547
	(0.193)	(0.303)	(0.242)	(0.342)
in yr prior 12 mo. ago	−0.149	−0.154	−0.082	−0.286
	(0.191)	(0.257)	(0.202)	(0.213)
***Mid-child life** experience: # of mo. with disaster*				
Between early life & recent yr.	−0.027	−0.029	−0.006	0.006
	(0.022)	(0.037)	(0.030)	(0.046)
***Early-life** experience: # of mo. with disaster*				
in the first 1000 days	−0.036**	−0.057**	−0.003	−0.030
	(0.017)	(0.029)	(0.026)	(0.040)
Observations	49,274	49,274	49,274	49,274

Note: This table shows regression results of Eq. (3) using a subsample of children whose mothers' duration of residence in the location exceeds the child's age. We use the mother's reported duration of residence and location to identify children whose entire lives have been spent in the same location as their mother. Each column shows results from separate regressions. All regressions include within-country location fixed effects, interview year fixed effects, interview month fixed effects, child age fixed effects, and attainment-country fixed effects. Standard errors, clustered at the within-country location level, are reported in parentheses. We do not apply probability weights applied to the survey designs of MICS6. * Significant at the 10 percent level. ** Significant at the 5 percent level. *** Significant at the 1 percent level.

Table C.13: Sample and population size for each country and dataset

Country	Year	Population aged 5-19 (million)	MICS dataset	Sample size	Sum of *fsweight*
Bangladesh	2019	49.877	BGD2019	40,617	66,705
Kyrgyz Republic	2018	1.856	KGZ2018	3,897	7,491
Mongolia	2018	0.866	MNG2018	7,628	12,287
Nepal	2019	9.081	NPL2019	7,824	14,293
Pakistan (Khyber Pakhtunkhwa)	2019	12.572	PKK2019	19,379	61,103
Pakistan (Punjab)	2017	38.953	PKP2017	37,052	94,748
Pakistan (Sindh)	2018	16.946	PKS2018	14,690	40,634
Thailand	2019	12.950	T172019	8,823	11,967
			THA2019	785	1,669
Turkmenistan	2019	1.801	TKM2019	3,776	7,788

Note: This table shows the information used to generate the sampling weight variable for each individual in the sample as discussed in the Appendix A. First, for each specific country (region) and year, we present the size of the population aged 5-19. These are the values of $ChildPop_c$. The values are obtained from https://www.populationpyramid.net/. For Pakistan, the raw sample weight variable *fsweight* is generated at the province-year level. However, we do not have direct measure of children population of each province. Hence, we calculate the children population size of each province as the population aged 5-19 in the country divided by the total population of the country, multiplied by the total population of the province. The population size of Khyber Pakhtunkhwa in 2017 is 35.5 million; Punjab in 2017 is 109.99 million; and Sindh in 2017 is 47.85 million. The population aged 5–19 for the entire country is 80.366 million, while the total population of the country is 226.929 million. For Thailand, the raw sample weight variable *fsweight* is generated at the country-year level. Second, we present the number of observations in the raw datasets of children aged 5-17 for each country (region). Finally, we present the sum of the sample weight variable (*fsweight*) in each dataset. These are the value of $\sum_{i=1}^{N_c} fsweight_{ic}$.

Table C.14: Summary statistics for all children (sample weights applied)

	Mean	SD	Min	Max	N
Panel A: Enrollment, math-test scores, attainment					
Ever enrolled (dummy)	0.89	0.31	0	1	140,750
Enrollment in last school year t-1 (dummy)	0.76	0.43	0	1	140,724
Enrollment in this school year t (dummy)	0.80	0.40	0	1	140,735
Have math Score (dummy)	0.92	0.27	0	1	85,603
Math score (total)	14.67	7.25	0	21	78,695
Attainment (highest)	3.33	3.20	0	16	140,695
Attainment at start of last school year t-1	2.71	2.94	0	16	140,696
Attainment at start of this school year t	3.30	3.19	0	16	140,695
Panel B: Child and parental characteristics					
Age of child	10.57	3.61	5	17	140,788
Female (dummy)	0.49	0.50	0	1	140,788
Mother ever educated (dummy)	0.60	0.49	0	1	140,726
Mother has secondary sch education (dummy)	0.31	0.46	0	1	140,726
Mother is living in same HH (dummy)	0.91	0.29	0	1	140,546
Father is living in same HH (dummy)	0.81	0.39	0	1	140,398

Note: This table is equivalent to Table 2 with sample weights applied. The sample weight variable used here is generated as *(fsweight/sum of fsweight*pop size)*.

Table C.15: Summary statistics of disaster exposures for all children (sample weights applied)

	Mean	SD	Min	Max
Panel A: Any disasters				
Had disaster				
in most recent 12 mo.	0.52	0.50	0	1
in year prior to 12 mo. ago	0.63	0.48	0	1
# of mo. with disaster				
in mid-child life	10.40	11.11	0	60
in the first 1,000 days (early life)	3.26	3.97	0	24
Panel B: Floods				
Had disaster				
in most recent 12 mo.	0.29	0.46	0	1
in year prior to 12 mo. ago	0.54	0.50	0	1
# of mo. with disaster				
in mid-child life	3.52	4.39	0	23
in the first 1,000 days (early life)	1.44	2.21	0	11
Panel C: Severe disasters				
Had disaster				
in most recent 12 mo.	0.24	0.43	0	1
in year prior to 12 mo. ago	0.34	0.48	0	1
# of mo. with disaster				
in mid-child life	4.01	4.72	0	33
in the first 1,000 days (early life)	1.60	2.52	0	24
Panel D: Severe floods				
Had disaster				
in most recent 12 mo.	0.19	0.40	0	1
in year prior to 12 mo. ago	0.27	0.44	0	1
# of mo. with disaster				
in mid-child life	2.36	2.94	0	20
in the first 1,000 days (early life)	0.97	1.82	0	11

Note: This table is equivalent to Table 3 with sample weights applied. The sample weight variable used here is generated from *(fsweight/sum of fsweight*pop size)*.

Table C.16: Summary statistics for all children (sample weights applied)

	Mean	SD	Min	Max	N
Panel A: Enrollment, math-test scores, attainment					
Ever enrolled (dummy)	0.85	0.35	0	1	140,750
Enrollment in last school year t-1 (dummy)	0.72	0.45	0	1	140,724
Enrollment in this school year t (dummy)	0.76	0.43	0	1	140,735
Have math score (dummy)	0.92	0.28	0	1	85,603
Math score (total)	13.01	7.57	0	21	78,695
Attainment (highest)	3.18	3.29	0	16	140,695
Attainment at start of last school year t-1	2.59	3	0	16	140,696
Attainment at start of this school year t	3.14	3.27	0	16	140,695
Panel B: Child and parental characteristics					
Age of child	10.59	3.69	5	17	140,788
Female (dummy)	0.49	0.50	0	1	140,788
Mother ever educated (dummy)	0.51	0.50	0	1	140,726
Mother has secondary-school education (dummy)	0.26	0.44	0	1	140,726
Mother is living in same household (dummy)	0.94	0.25	0	1	140,546
Father is living in same household (dummy)	0.84	0.37	0	1	140,398

Note: This table is equivalent to Table 2 with sample weights applied. The sample weight variable used here is generated as *fsweight* from MICS data.

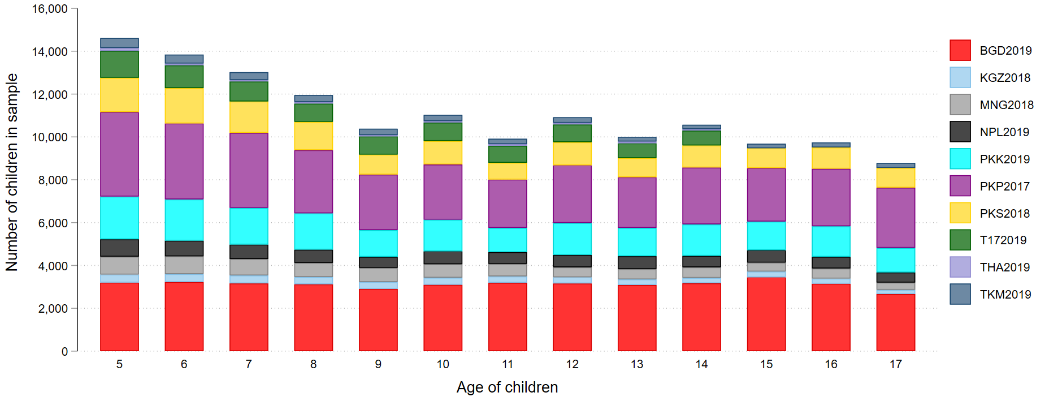
Table C.17: Summary statistics of disaster exposures for all children (sample weights applied)

	Mean	SD	Min	Max
Panel A: Any disasters				
Had disaster				
in most recent 12 mo.	0.54	0.50	0	1
in year prior to 12 mo. ago	0.63	0.48	0	1
# of mo. with disaster				
in mid-child life	7.10	8.32	0	60
in the first 1,000 days (early life)	2.84	3.52	0	24
Panel B: Floods				
Had disaster				
in most recent 12 mo.	0.28	0.45	0	1
in year prior to 12 mo. ago	0.52	0.50	0	1
# of mo. with disaster				
in mid-child life	3.69	4.58	0	23
in the first 1,000 days (early life)	1.47	2.17	0	11
Panel C: Severe disasters				
Had disaster				
in most recent 12 mo.	0.31	0.46	0	1
in year prior to 12 mo. ago	0.31	0.46	0	1
# of mo. with disaster				
in mid-child life	3.77	4.38	0	33
in the first 1,000 days (early life)	1.35	2.21	0	24
Panel D: Severe floods				
Had disaster				
in most recent 12 mo.	0.16	0.37	0	1
in year prior to 12 mo. ago	0.13	0.34	0	1
# of mo. with disaster				
in mid-child life	2.29	2.91	0	20
in the first 1,000 days (early life)	0.88	1.66	0	11

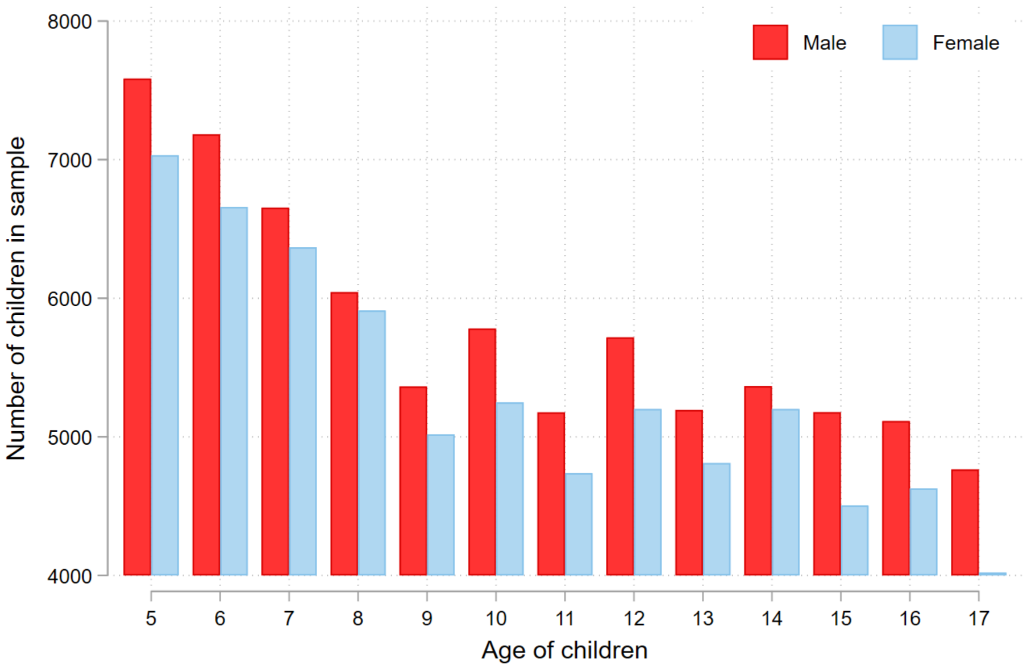
Note: This table is equivalent to Table 3 with sample weights applied. The sample weight variable used here is generated as *fsweight* from MICS data.

Figure C.1: Sample Sizes Across Countries, Ages, and Gender

(a) Sample Sizes Across Countries and Ages



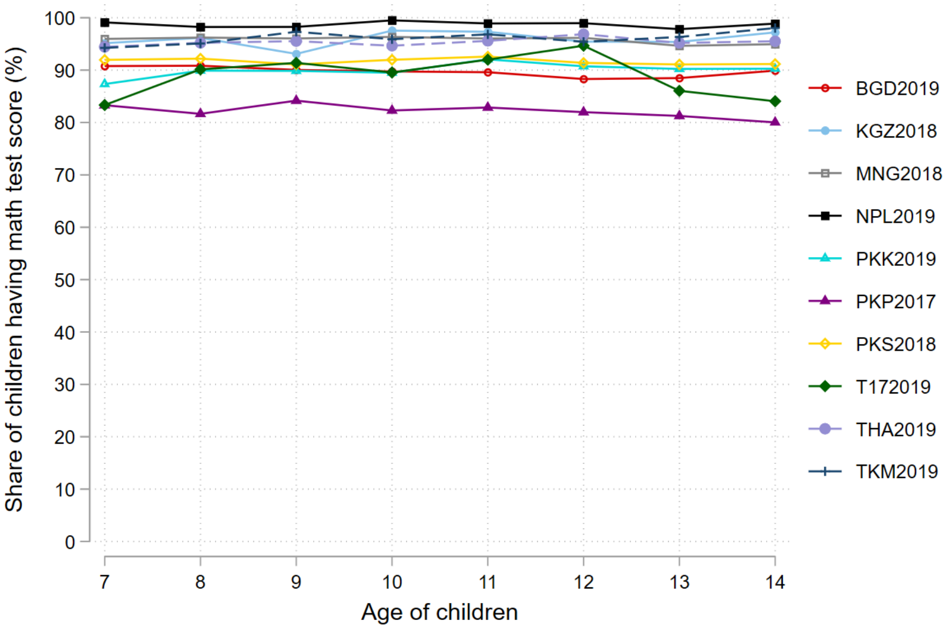
(b) Sample Sizes Across Gender and Ages



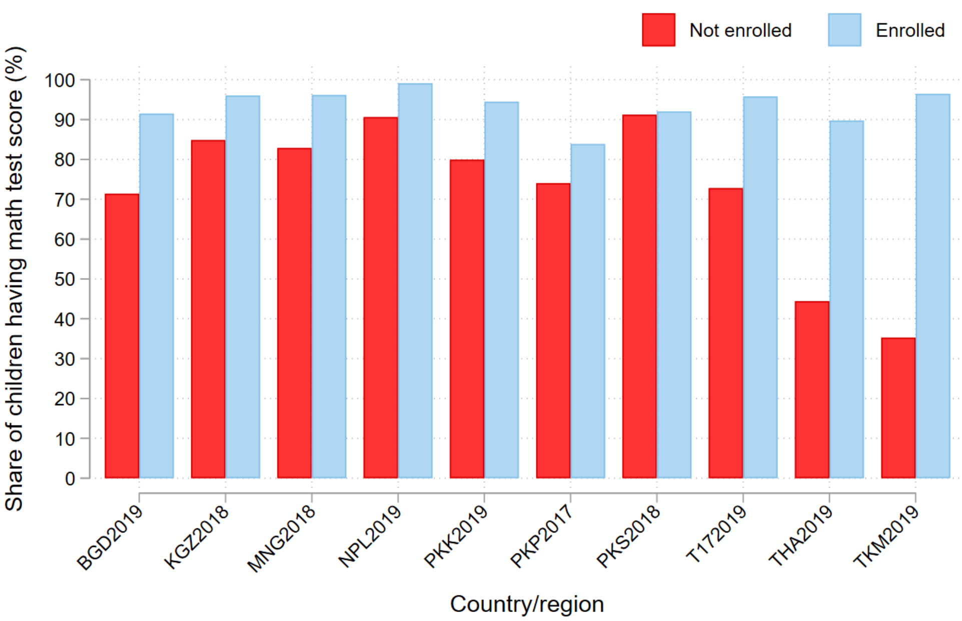
Note: Panel (a) shows the number of children for each age and country. There are 144,471 children in the full sample, dominated by Bangladesh and Pakistan. For every age and country, there are more boys interviewed than girls. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure C.2: Math Test Sample Size

(a) Math Test Sample Size by Age and Country



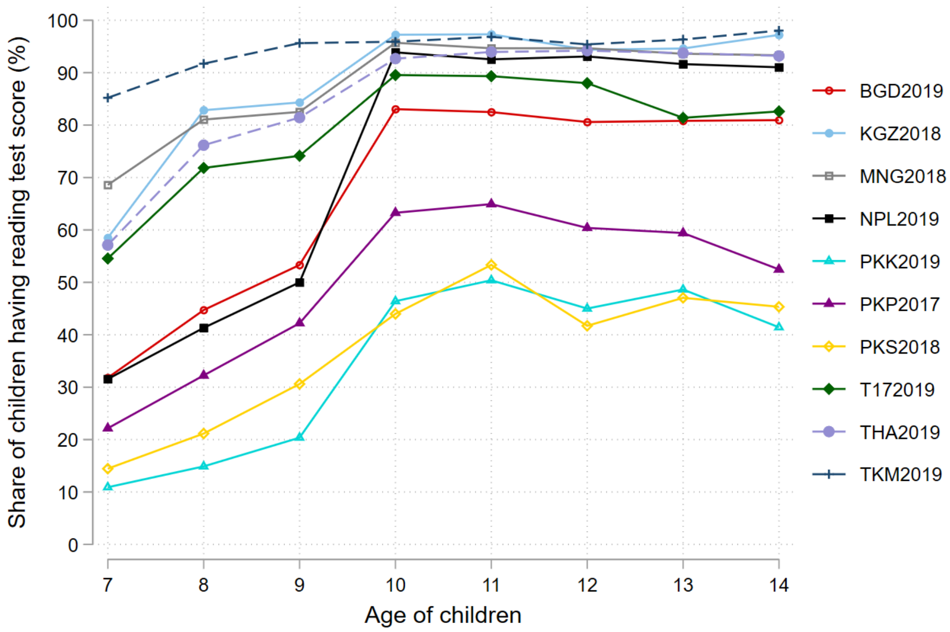
(b) Math Test Sample Size by Enrollment Status in Current Year Across Countries



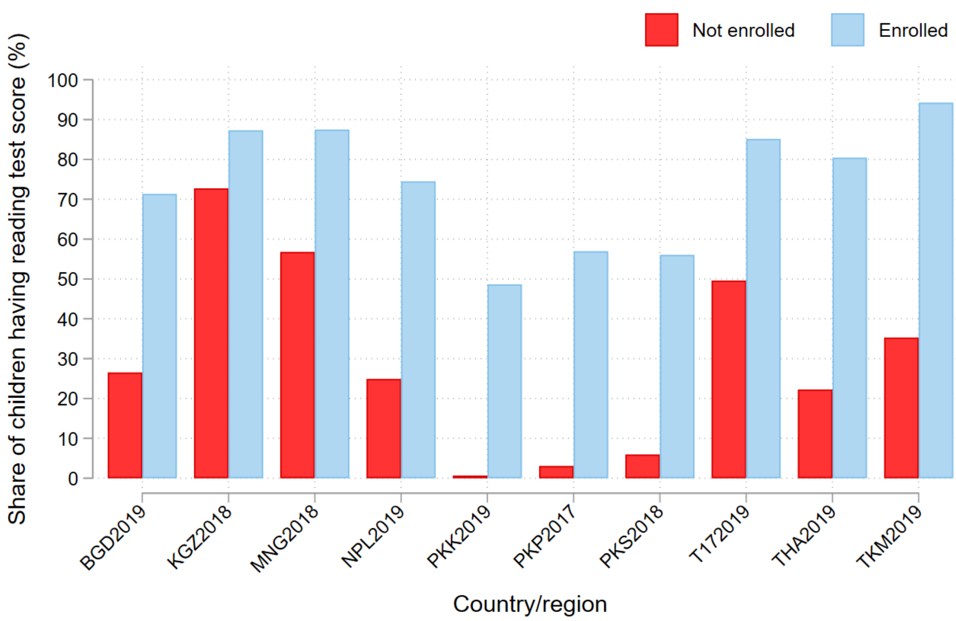
Note: Fractions show the shares of the sample by age and country reporting math scores, with consistent shares across ages and some variation across countries. We find much larger shares with math-test scores reported if the children are enrolled in school; they all exceed an 80% chance. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure C.3: Reading Test Sample Size

(a) Reading Test Sample Size by Age

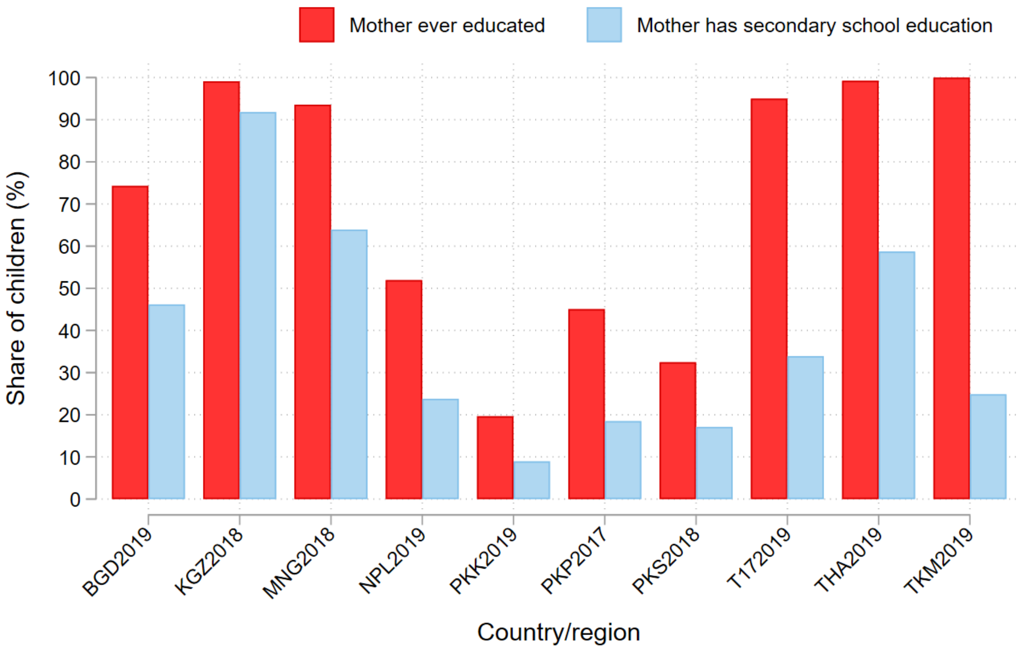


(b) Reading Test Sample Size by Enrollment Status Across Countries



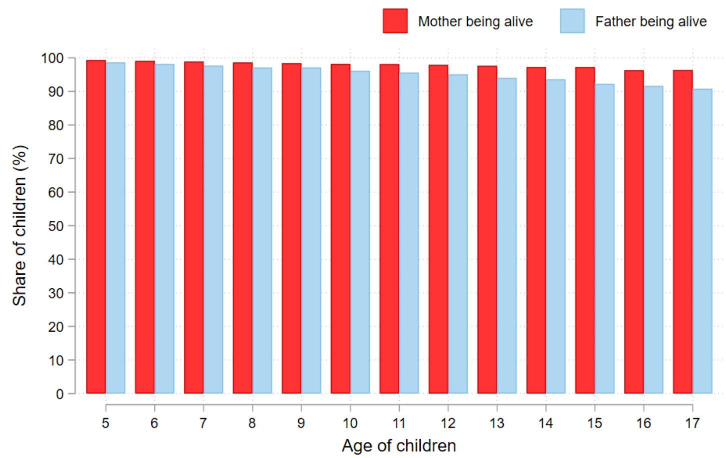
Note: Fractions show the shares of the sample by age and country reporting reading test scores, with consistent shares across ages and some variation across countries. We notice that whether the child has a reading test score is related to if she is enrolled in school in the current period. We find much larger shares with reading test scores if the children are enrolled in school; they all exceed an 80% chance. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure C.4: Share of Children Whose Mother Has Some Education

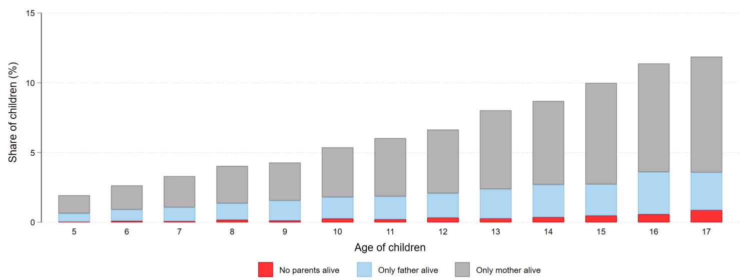


Note: This table shows (1) the share of children whose mother has had any kind of education and (2) the share of children whose mother has secondary school education by country. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

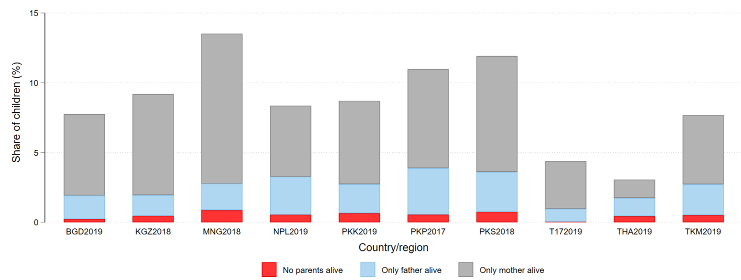
Figure C.5: Share of Children with Mother or Father Alive by Age



(a) Share of Children with Mother or Father Alive by Age



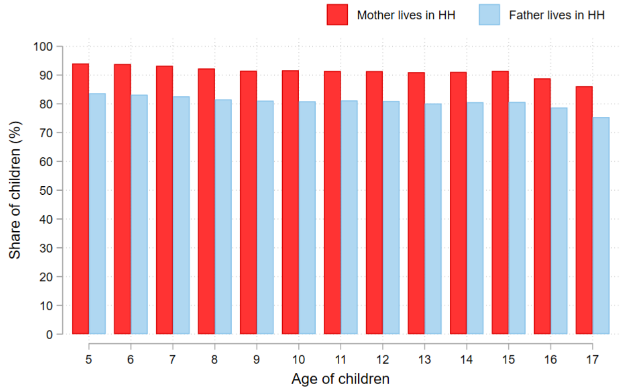
(b) Share of Children with One or Both Parents Alive by Age



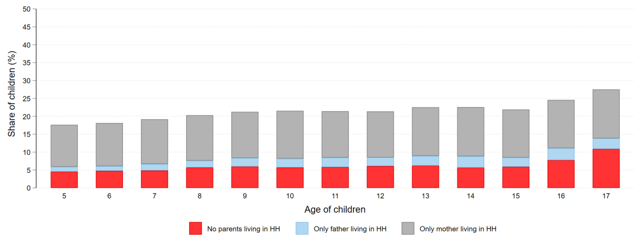
(c) Share of Children (Age $\geq$ 12) with One or Both Parents Alive by Country

Note: Panel (a) shows the share of children with a mother or father who is alive by age. Panels (b) and (c) show the share of children from 12-17, by age or by country, respectively, with both parents alive (not included in the bar), with just the mother alive, with just the father alive, and with both parents not alive.

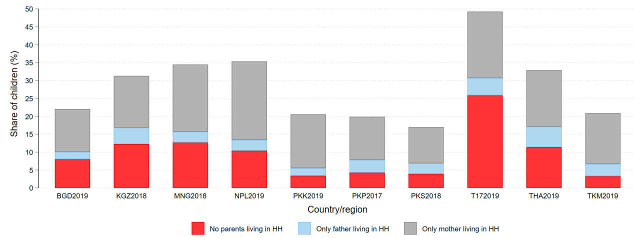
Figure C.6: Share of Children Living with Parents



(a) Share of Children Living with Mother or Father by Age



(b) Share of Children Living with One or Both Parents by Age

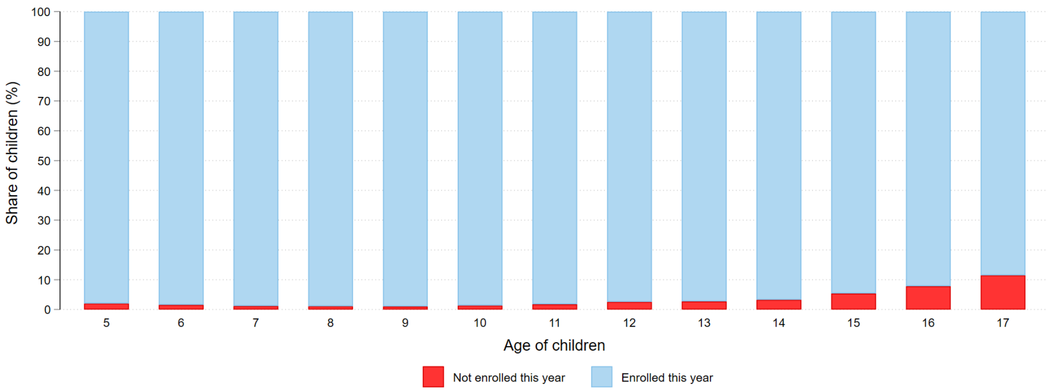


(c) Share of Children (Age $\geq$ 12) Living with One or Both Parents by Country

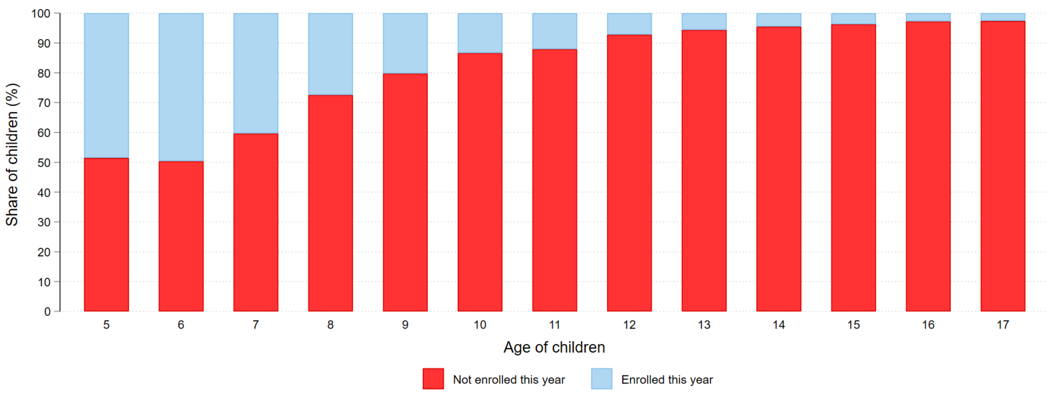
Note: Panel (a) shows the share of children living with either their mother or father by age. Panels (b) and (c) show the share of children living with both parents or one of them by age. The four categories include living with both parents (not included in the bar), living with just the mother, living with just the father, and not living with either parent.

Figure C.7: Enrollment Transition Probabilities by Age

(a) Enrollment Fraction in Survey Year Conditional on **Being Enrolled** in the Previous Year



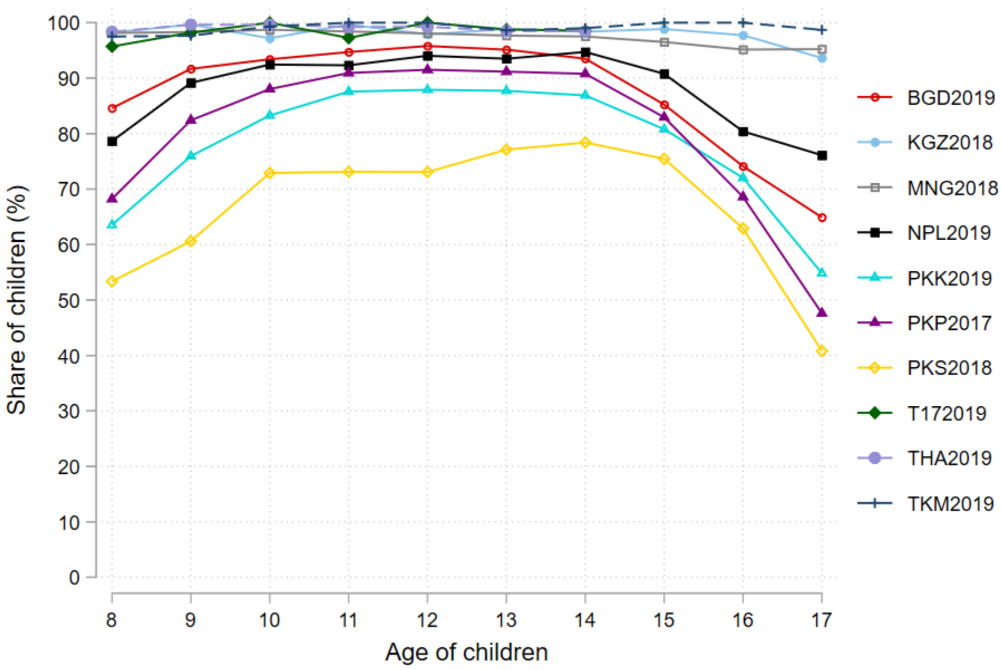
(b) Enrollment Fraction in Survey Year Conditional on **Not Being Enrolled** in the Previous Year



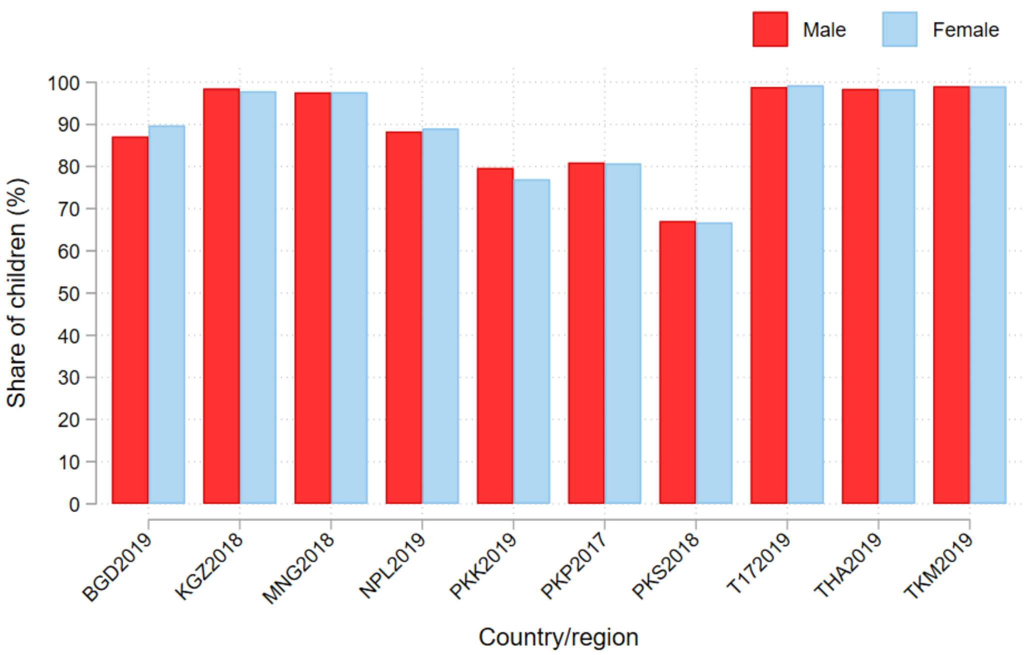
Note: Enrollment fraction in survey year conditional on being **enrolled** the previous year. The results show conditional probabilities.

Figure C.8: Distribution of Progression in Last School Year

(a) Progression Rate in Last Year by Age and Country



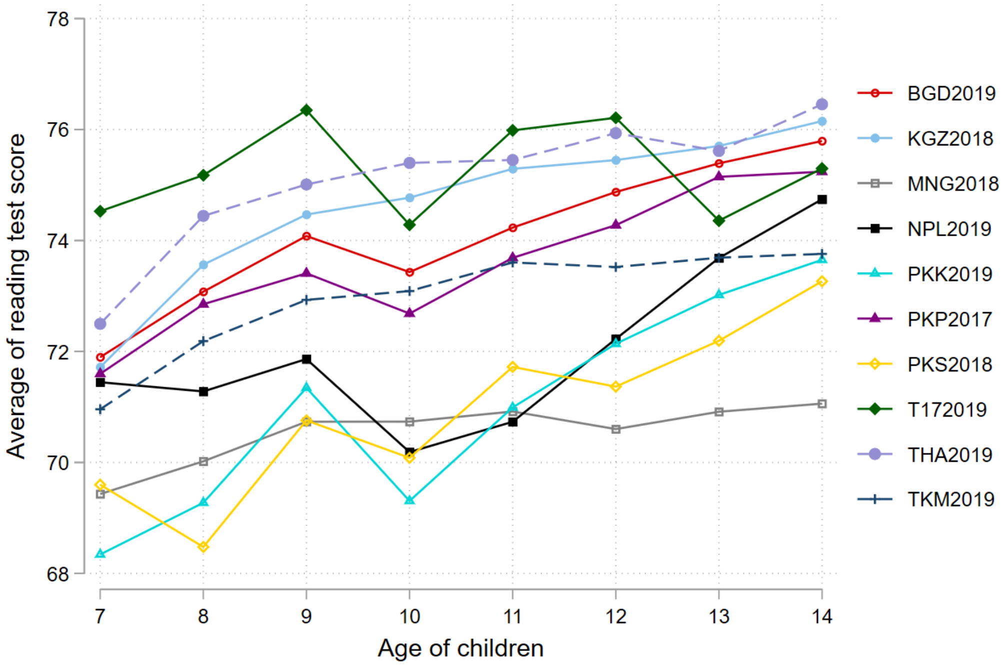
(b) Progression Rate in Last Year by Gender and Country (Age ≥ 8)



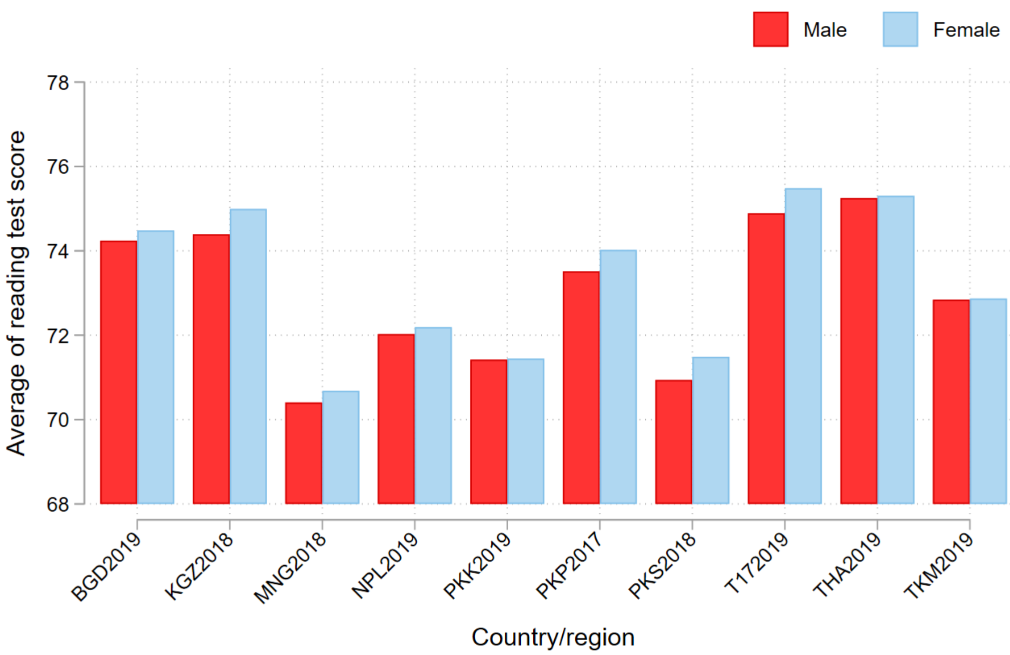
Note: The figure shows progression rates. The progression is equal to 1 if a child attends a grade and successfully completes the grade, leading to an increase in grade completion by 1 year. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure C.9: Distribution of Reading Test Scores

(a) Average of Reading Test Scores Across Ages and Countries



(b) Average of Reading Test Scores by Gender and Country (Age 7–14)



Note: Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).