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

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Abstract

We estimate natural-disaster impacts on children's school enrollments and math skills and test for impact heterogeneities with respect to age and gender in seven countries in Asia and the Pacific, which is the world's most disaster-prone region. We link survey data on children aged 5 to 17 to time- and geo-coded disaster variables. We create time-varying disaster exposures for each child for the first 1,000 days from conception, the most recent years, and the time in between. The results show significant negative effects of early life natural-disaster exposures on enrollments and math skills; weaker or no effects of recent or mid-childhood disaster exposures; persistent negative effects of early life exposures on enrollments through school-going ages; and variable age patterns of the enrollment and learning effects of exposures across countries. Boys' enrollments were more negatively affected by early life natural-disaster exposures, and girls' math-test scores were more negatively affected by early life natural-disaster exposures.

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). 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). Asia 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). 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). Studies of natural disasters' effects on children have focused on tracing the impacts of specific large-scale disasters (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). Most of these studies focus on the effects of natural disasters on child development through their health status, such as the studies on the fetal-origins hypothesis in the short and long run using data on the 1918 Influenza pandemic (Almond and Mazumder 2005; Lin and Liu 2014) or major droughts (Ciancio et al. 2023). Fetal loss and birth weights are found to be negatively affected by *in utero* exposure to natural disasters or extreme climatic events such as typhoons (Liu, Liu, and Tseng 2022b) and tornadoes (Gunnsteinsson et al. 2015). In the long run, these early life shocks have negative impacts on outcomes such as mental health in adulthood (Liu, Liu, and Tseng 2022a). It has also been reported that prenatal stress caused by exposures to natural disasters is linked with lower birth weights and lower gestational ages at delivery (Rondó et al. 2003; Sable and Wilkinson 2000; Torche 2011).

Relatively few studies investigate the impacts of disasters on educational outcomes. Those that do usually examine one disaster in one country rather than multiple types of disasters in multiple countries.[1] 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 educational attainment in adulthood was linked to high-

1. 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.

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 in children aged 0–2 who experienced the 2006 Yogyakarta earthquake in Indonesia (Hadiman and Djamaluddin 2022), and a study showing 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) show negative educational outcomes after large income shocks related to the 1987–89 locust plague in Mali. Gibbs et al. (2019) find that academic performance was reduced in schools with higher exposure to a major bushfire in Australia.

The impacts of climatic disasters on children's lives are multifaceted. Natural-disaster shocks may impact children's learning processes through schooling disruptions. 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).[2] In addition to their effects on school operations, disasters can lead to negative income shocks for households and health shocks for both parents and children. These shocks could cause unanticipated parental deaths, reduce household resource availability for schooling, reduce children's physical capacity to attend school, 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). Recent work by Adhvaryu et al. (2024) shows that grade attainment and post-secondary enrollment decline if children, in their early years, experience adverse rainfall, an event lowering the agricultural wage and affecting children's physical health.

While the aforementioned reasons would tend to reduce enrollments under disasters, for some children, the effects might also go in the opposite direction: 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).

In this paper, to our knowledge, we provide 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. Specifically, 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 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 temperatures. Exploiting variations in MICS survey locations and variations in

2. 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 do not study the effects of the COVID-19 pandemic on educational outcomes.

location-specific survey timing, as well as age variations among the children surveyed in each location and each month, we develop a novel dataset that provides time-, age-, and location-specific disaster exposure histories for children surveyed in MICS in their respective countries.[3]

We investigate the impacts of exposure to natural disasters on human-capital accumulation. 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. 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). 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.[4] Health problems early in life could exert long-term negative impacts on the cognitive development of children. These circumstances could also raise the cost of children attending schools, compared to their healthier peers, if they need more specialized education and more medical attention, and if they are more likely to miss classes.

We estimate the impacts of natural disasters on school enrollments and human-capital accumulation as measured by math skills for children. In particular, utilizing our novel panels of child-specific disaster-exposure histories, 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.

To address our research questions, we estimate two empirical models. 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 enrollment decision as a function of prior attainment, prior enrollment, and parental characteristics, along with children's recent and earlier disaster-exposure histories. To explore effect heterogeneity moderated by permanent child- and household-specific factors, we allow combinations of interactions between natural disasters and

3. In addition to considering all types of disasters, which are used to construct type-A disaster-exposure intensities, we also show results considering only floods (type B), only severe disasters (type C), and only severe floods (type D). Severe disasters are defined as causing more than 500 deaths or injuries or affecting at least 5,000 people.

4. 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).

gender, age, and country while controlling for parental conditions. 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). Our unique data on children's disaster histories allow us to jointly consider the effects of all prior and recent disasters over the life of each child. 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 exposures on enrollment status, but weaker or no corresponding effects related to recent disaster exposures. Heterogeneity analysis shows that there are persistent negative effects of early life natural-disaster experiences on enrollments through the primary-school-going ages for boys but weaker effects for girls. The effects from exposures to natural disasters on math-test scores are also weak for recent shocks yet strong for exposures in early life. Although boys suffer more than girls in terms of enrollment status due to early life disaster exposures, in the current performance on math tests, the negative effects of early life disasters are more persistent for girls than boys at older ages (13 to 14). The findings in this paper are based on the children surviving the natural disasters. Given this positive selection, the negative effects of early childhood natural-disaster exposures on educational outcomes are probably underestimated.

These findings contribute to the existing literature showing that impacts in early life have a gender-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 et al. 2004; Cameron and Worswick 2001), and cognitive skills (Chang, Favara, and Novella 2022). This is 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). Our findings focus on longer-run impacts and add to the existing literature studying educational outcomes. For example, Wu, Lin, and Han (2023) show that positive rainfall shocks in birth years increase long-term test scores and educational attainment for girls, but not for boys. Nübler et al. (2021) find that adolescent girls are more negatively affected by local rainfall shocks in early life and at school-starting ages.

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 country- 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.

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] Table 1 provides country-specific data-collection windows, sample sizes, and summary statistics for some key variables.

2.2 Data on Disasters

Our natural-disaster variables are constructed from the EM-DAT database (1900–2023) (Delforge et al. 2023). We match individual MICS6 survey dates, as well as the smallest unit of geo-identifier possible, with the time- and geo-coded disasters.

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 loss 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

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

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.

(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 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 data due to the relatively limited availability of these variables.

2.3 Measures

2.3.1 Parental and Household Characteristics

For socioeconomic status (SES), we consider the parents' ages, 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 match the biological mother and father to each child to obtain their demographic details. 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 Outcomes

The educational outcomes that we consider are school enrollments for children aged 5 to 17 and math-learning skills for children aged 7 to 14.[7] We show the average enrollment rates at the regional level[8] for each country in Table 1. 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. 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.

2.3.3 Disaster Shocks

Location and Migration. We assume that children do not move and have resided since conception in the current location recorded in MICS. While the migration history of children is not observed, it is feasible to identify the biological mothers of the children in our sample from the eligible-women-survey module and extract the migratory history utilizing two pieces of information: years living in the current location and years living in the prior location, which might be recorded at a different administrative level.[9]

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. There are two key reasons that mothers' migration information is not available for the full sample. First, the Pakistan Khyber Pakhtunkhwa Province (denoted as "PKK") women module does not contain migration variables. Second, only women aged 15 to 49 are surveyed separately in the women module, but the natural mothers of children in the sample may be older.

The first-level and second-level administrative divisions are large in each country and most migrations are likely within these divisions (Bangladesh Bureau of Statistics (BBS) and UNICEF Bangladesh 2019; Bureau of Statistics 2021). Among the sample for which we do have migration information, we find that, across countries and on average, mothers have resided at their current location for 92% to 98% of the years since the birth of their child selected for the

7. 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%, so we do not investigate reading scores in this paper.

8. 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.

9. For Bangladesh, we know the names of second-level administrative divisions (districts) as current locations for mothers and children. However, we only observe first-level administrative divisions (division) for prior locations of mothers. For the Kyrgyz Republic, we know first-level administrative locations (Oblast) for both current and prior locations of mothers. For Mongolia, first-level administrative locations (aimag) are observed for both current and prior locations of mothers, but not for children. For Nepal, first-level administrative locations are collected for both mothers and children. For Pakistan, like Bangladesh, second-level administrative locations (districts) are observed for current locations of mothers and children, but the prior location information is only available at the first administrative level. For Thailand, there is also finer information for the current locations of mothers (region and Changwat), but only regional names for prior locations. For Turkmenistan, first-level administrative (region or province) location names are collected for current and prior locations of mothers.

5 to 17 Child Questionnaire. Furthermore, across countries and on average, between 83% and 96% of the mothers have not moved since the birth of their child selected for the 5 to 17 Child Questionnaire. Given these patterns, our location history, constructed under the assumption that children have not moved since conception, captures fairly well the actual location history experiences 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 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.[10] 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 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.[11] The

10. While early life exposure age-in-months (e.g., 1st, 2nd, 3rd month after birth) windows would be homogeneous across children, 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}.

11. 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.

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. For the disaster-intensity type indexed by p, we define type A to include any type of disaster, type B to include only floods, and type C to include severe disasters, defined as causing more than 500 deaths or injuries or affecting 5,000 people or more. Type D is the overlap between types B and C to consider only severe floods. In the main results, we consider the effects of exposures to disasters of types A, B, C, and D, and we present them in successive columns of our regression tables. Having various types of disaster intensities provides the possibility of robustness checks on disaster experience construction. Out of a total of 355 disaster events, 155 were categorized as floods, included in the type B disaster classification. Severe disasters accounted for 174 out of the 355 events, forming the basis for the type C disaster intensity. Within this subset, floods emerged as the most frequent event, with 93 incidents, which were subsequently classified under the type D disaster intensity.

3 Summary Statistics

3.1 Summary Statistics for Children and Parents

3.1.1 Sample

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. 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 in three 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 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.

3.1.2 Parental and Household Characteristics

Table 2 shows that fathers' ages are on average 6 years greater than mothers' ages, and the percentages of fathers having any education are slightly higher than these percentages for mothers. However, it is also noticeable that father information is collected for a smaller sub-sample than mother information. We find larger shares of children co-residing with mothers than with fathers and more mothers who are alive than fathers, and Figure 2 presents 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 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 Appendix Table C.2 and Figure C.3, we break down the sample by country and show information on mothers' educational 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.[12] 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.

3.1.3 Educational Outcomes

In Panel A of 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 3, 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 3, 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 the preceding year, generally go up for children up to 10 years of age and then decline for older children in all countries. We also present in Figure 4 the shares of children who have ever been enrolled in school, which are increasing with age. These rates reach close to 100% of the samples by age 8 in all countries except for Pakistan, where over 30% of children aged 17 are never enrolled in Sindh Province in our sample.

Across countries, we also find that the chance of non-enrollment is significantly higher if a child was not enrolled in the previous year. Specifically, Figure 5 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.

12. According to a report on Pakistan from 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.

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 6. The average attainment for children (5–17 years old) varies by country, with Mongolian children having the highest average attainment and children from Pakistan 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-skill-test results by age and country are shown in Table 3 and Figure 7. Compared to other countries, aggregate math scores are lower in Nepal and Bangladesh 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 7, 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 the 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.

3.2 EM-DAT Disaster Experience

With the linked MICS and EM-DAT disaster-exposure data, we consider the share of children from the MICS sample who have experienced disasters identified by EM-DAT. The last panel of Table 2 shows that 55% of children in the seven countries experienced disasters in the 12 months prior to the interview months, 63% of children experienced disasters between 24 and 13 months prior to the interview months, and 77% of children experienced disasters between 10 years and 25 months prior to the interview months. In Table 4, furthermore, we show variations in disaster exposures across countries. Mongolia, Bangladesh, and Pakistan have high recent exposure rates, with 86%, 68%, and 62% of children experiencing disasters in the 12 months prior to the interview months, respectively.

Additionally, we show in Figure 8 the shares of location-months experiencing disasters of different types by calendar month and country. The results indicate a higher prevalence of disasters 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 jointly exploiting temporal and spatial variations in disaster exposures. We model 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. 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 $m12t1$ 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 parental ages, 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 also survey-time fixed effects μ_t.[13] 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 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 het-

13. 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.

erogeneous 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 $\beta^p_{g_i(m),j}$:

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

where $\beta^p_{g_i(m),j}$ 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 $\beta^p_{g_i(m),j}$ 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

In this section, we present estimation results. From an 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.

5.1 Enrollments and Disaster Experiences

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. Following our discussions of the enrollment-decision model, in all columns of Table 5, we include lagged enrollments from the prior school year (enrollments in year $t-1$), as well as the attainment (grade of schooling) completed at the start of the current school year (at the start of t); due to differences in age-specific schooling trajectories across countries, we allow the effects of prior enrollments and attainments to differ by age and country. Additionally, we control for child, parental, and household characteristics, including the child being female, parental survival, and the parent-child co-residency status, and if the mother has ever been to school and has secondary schooling. For all results, we control for location, calendar-time, and child-age fixed effects.

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.

In columns (2) to (4), 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 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.

Across the columns, we find strong positive associations between current enrollments and lagged enrollments and attainment (see Appendix Table C.4). 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 an additional reduction in enrollments by 0.5 percentage points.

5.2 Heterogeneous Effects on Enrollments Across Ages and Genders

In this section, we continue to estimate Eq. (2) using linear probability models, but we explore heterogeneity by child-age groups in Table 6 and heterogeneity by joint child age and gender groups in Table 7. In both tables, we present the results in four columns, focusing on exposures to any disasters, floods, severe disasters, and severe floods. Age groupings are defined based on the age range for primary-school education across different countries. The 5-to-8 age group corresponds to initial enrollment and lower-primary grades, the 9-to-12 age group corresponds to upper-primary grades, and the 13-to-17 age group corresponds to post-primary secondary-school grades.[14]

In Tables 6 and 7, compared to the overall weak negative results for all children from Table 5, we find stronger negative effects of exposure to recent disasters on enrollments for children during the upper-primary and post-primary ages (9 to 17), with larger impacts for boys. 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, with recent-severe-flood exposure reducing enrollments for boys 9 to 17 by more than 3 percentage points. For children 5 to 8, we find that recent-flood exposures lead to a 2-percentage-point reduction in enrollments. However, recent-severe-flood exposures lead to a 3.6-percentage-point increase in enrollments. It is plausible that in some settings, schools might be safe and resourceful locations for young children during times of severe disasters due to the ease of coordinated and centralized disaster-relief efforts and the risks of staying in damaged homes.

Similar to the recent-disasters results, we also find consistent negative direct effects of early disaster experiences on enrollments for children 9 to 17, with upper-primary boys experiencing the strongest effects—an additional month of early disaster exposure reduces their enrollments by 0.3 percentage points, triple the average effects for all children from Table 5. Table 7 also shows that for children 9 to 17, an additional month of early life exposure to floods, severe disasters, and severe floods leads to up to 0.4-percentage-point reductions for boys'

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

current enrollments and a 0.3-percentage-point reduction for girls' enrollments. Interestingly, we find negative direct effects of early disaster exposures on enrollments for girls 5 to 8 but no effects for boys, which indicates an early disaster exposure penalty for girls during primary-school starting ages.

The existing literature suggests that gender plays multiple roles in educational decisions in low- and middle-income countries. For example, a study of a locust plague in Mali finds that school enrollments are reduced by 2.8 percentage points for boys born at the time of the natural disaster, while girls are found to experience negative impacts purely on attainment measured by grades of schooling (De Vreyer, Guilbert, and Mesple-Somps 2015). In Guatemala, girls, but not boys, are found to increase their schooling attainment in response to early-life enhanced nutritional supplements, with the authors conjecturing that for older boys, the opportunity costs of working instead of attending school increased with better nutritional status (Maluccio et al. 2009). On the other hand, in some areas of Pakistan, males are favored in the allocation of educational resources, leading to gender disparities in educational attainment (Raza, Shah, and Haq 2022). Because disaster shocks can induce short- and long-run income shocks, it is plausible that in some contexts upper-primary- and post-primary-aged children, particularly boys, might drop out of school to help with income generation. This would be consistent with our findings of larger negative disaster exposure effects for relatively older boys and with a few studies, such as the Guatemalan one, suggesting higher opportunity costs for schooling for older boys.

To complement the main results, in Appendix Table C.6, we present separate estimates for children in the 5–8, 9–12, and 13–17 age groups from Pakistan, Bangladesh, and other countries. The results largely echo our findings on overall and age-specific effects. For Pakistan, we find negative impacts from exposure to recent disasters on enrollments in all three age groups, as well as negative impacts of direct early life disaster exposure on enrollments, but more significantly for children 5 to 8. For Bangladesh, we find that both recent and early disaster exposures have sharp age gradients, with growing negative effects of both recent and early disasters on enrollment as children age.

5.3 Math Skills and Disaster Experiences

In Table 8, 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. Following the presentation of the enrollment results, Table 8 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 7), which vary between 0 and 21 points.

Averaging across children 7 to 14, Table 8 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 3), 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.

The estimated average effects of disaster exposures on math skills by disaster type are shown in columns (2) to (4) of Table 8. We find that while floods have no significant impact during recent life stages and only weak negative effects during mid-child life 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.

Additionally, we find consistent patterns of relationships between child, parental, and household characteristics and math-test scores across the columns of Table 8. 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.

5.4 Heterogeneous Effects on Math Skills Across Ages and Genders

In this section, we estimate the heterogeneous effects of life-cycle disaster exposures on math scores by age group in Table 9 and by joint age and gender group in Table 10. As before, we present results across disaster types in four columns. 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 in Tables 9 and 10. Additionally, while the results are not precisely estimated, 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.

In Tables 9 and 10, we find that early life disasters' negative effects on math-test scores for lower-primary and post-primary children are similar in magnitude compared to the average effects from Table 8. 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 10, across disaster types, we continue to find consistently negative but generally imprecisely estimated early life disaster exposure effects for lower-primary and post-primary children, with more persistent negative effects on older girls. Specifically, 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 8. 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.

Generally, compared to later disaster exposures, we find that early disaster exposures have larger negative effects across age and gender groups on math-test scores. 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 cognitive underdevelopment, and strong correlations between height and test scores in both developing and developed countries are observed (Case and Paxson 2010; Glewwe, Jacoby, and King 2001; Glewwe and King 2001; Hoddinott et al. 2013).

In Appendix Table C.8, we estimate heterogeneous effects by country and age groups. 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. Additionally, we find negative effects of early life disaster exposures on math-test scores for children in Pakistan, but not in Bangladesh. The results for other countries are generally imprecisely estimated. Given age-composition and disaster-history differences across countries, there are insufficient within-country variations in early and mid-child life exposure histories to pin down country-, life-cycle-, and age-specific exposure effects.

6 Conclusions

A 2023 report from UN-ESCAP (2023) indicates that climatic change-induced disasters pose an increasingly serious threat to Asia and the Pacific, the most natural-disaster-prone world region. As disaster resilience becomes an important policy concern in educational sectors, particular attention is given to its impact on children, who are especially vulnerable. This paper focuses on estimating disaster effects on children's educational outcomes in seven countries in Asia, with an emphasis on exposures in the first 1,000 days from conception, middle childhood, and the period immediately preceding the surveys and tests. 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, we contribute to a large body of literature addressing the immediate and lasting effects of disaster shocks in early life on children's human-capital outcomes, although much of the previous literature is on health and nutritional status, not educational outcomes. Second, we explore regional and local heterogeneity, 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 exploit cross-location and cross-time variations in disaster exposures across children, and our results provide a broader perspective than studies limited to single countries. Third, 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 very different countries. We find, nevertheless, that one type of disaster, namely floods, tends to have the largest effects on educational outcomes.

Our results show, overall, significant negative effects of early life disaster exposures on enrollments and math skills, but weaker or no corresponding effects from recent disaster exposures. There is a persistent negative relationship between early life disaster experiences and enrollments through the school-going ages. Both boys and girls are affected negatively by exposure to natural disasters in early life in terms of educational outcomes, but with some differences by gender. Although boys are vulnerable in terms of school enrollments to having experienced natural disasters in early life, girls' performances on MICS-administered math tests are harder hit by early life natural disaster exposures than boys' performances on these tests. Additionally, we show that exposures to floods in particular, but also to severe disasters and severe floods, generally have larger negative effects than exposures to "all disasters."

In directly using school enrollment and test score data for children, this paper is one of the few studies to establish the lasting effects of having experienced natural disasters in the first 1,000 days on schooling enrollments and learning outcomes. These findings highlight the need to more specifically support children affected by disasters, perhaps particularly floods, in their early years.

Tables and Figures

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

	Survey timeframe			Obs	Geo info		Enrollment
	Year	Start date	End date		Geo-identifier‡	N	Fraction
South Asia							
Bangladesh	2019	01/19	06/01	37925	District	64	0.89
Nepal	2019	05/04	11/13	7618	Region	7	0.93
Pakistan	2017-19	2017 12/03	2019 10/23	54072	District	97	0.86
East and Southeast Asia							
Mongolia	2018	09/17	12/24	7277	Region	5	0.96
Thailand	2019	05/18	12/03	9429	Changwat	18	0.99
Central Asia							
Kyrgyz Republic	2018	09/06	11/19	3754	Oblast	9	0.96
Turkmenistan	2019	05/02	08/02	3410	Region	6	1.00

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	0.88	0.33	0.00	1.00	144426
Enrollment in last school year t-1	0.74	0.44	0.00	1.00	144394
Enrollment in this school year t	0.79	0.41	0.00	1.00	144410
Have math score	0.90	0.30	0.00	1.00	87,797
Math score (total)	14.09	7.37	0.00	21.00	78,704
Attainment (highest)	3.29	3.34	0.00	16.00	144358
Attainment at start of last school year t-1	2.69	3.06	0.00	16.00	144360
Attainment at start of this school year t	3.25	3.32	0.00	16.00	144358
Panel B: Child, parental, and household characteristics					
Age of child	10.49	3.78	4.00	17.00	144471
Female	0.48	0.50	0.00	1.00	144471
Mother's age	37.78	8.68	2.00	95.00	132143
Father's age	43.06	9.70	0.00	95.00	116791
Mother ever educated	0.58	0.49	0.00	1.00	144338
Mother has secondary-school education	0.31	0.46	0.00	1.00	144338
Father ever educated	0.69	0.46	0.00	1.00	116768
Father has secondary-school education	0.20	0.40	0.00	1.00	116768
Mother is living in same household	0.92	0.28	0.00	1.00	144222
Father is living in same household	0.81	0.39	0.00	1.00	144068
Panel C: Location-specific and child-life-cycle-specific disaster history					
Had recent disaster (DB^A) ...					
in survey month	0.08	0.27	0.00	1.00	144471
in year prior to survey month	0.55	0.50	0.00	1.00	144471
in year prior to 12 months ago	0.63	0.48	0.00	1.00	144471
Had disaster at least once in location-specific disaster history (DB^A) ...					
between 10 years ago and 2 years ago	0.77	0.42	0.00	1.00	144471
Had disaster at least once given child-life-cycle-specific disaster history (DB^A) ...					
in child's first 1,000 days of life (early life)	0.58	0.49	0.00	1.00	144471
between early life and 2 years before survey month (mid-child life)	0.70	0.46	0.00	1.00	144471

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, and location-specific or child-and-location-specific disaster experience indicators in the third panel. DB^A is an indicator equal to one if there is any type of disaster in the designated time span, and it is equal to zero if not. For example, DB^A being equal to one in a survey month means there was a disaster in the month when the child was surveyed. In the total sample, 8% of children had any type of disaster in the survey month.

Table 3: Summary statistics for educational outcomes by country

	Mean	SD	Min	Max	N
Bangladesh					
Enrollment in this school year t	0.85	0.36	0.00	1.00	40,617
Enrollment in last school year t-1	0.79	0.41	0.00	1.00	40,616
Attainment (highest)	3.91	3.20	0.00	14.00	40,614
Math score	16.32	5.87	0.00	21.00	22,354
Kyrgyz Republic					
Enrollment in this school year t	0.93	0.25	0.00	1.00	3,897
Enrollment in last school year t-1	0.90	0.30	0.00	1.00	3,897
Attainment (highest)	3.91	3.38	0.00	13.00	3,897
Math score	19.40	2.70	0.00	21.00	2,349
Mongolia					
Enrollment in this school year t	0.94	0.24	0.00	1.00	7,627
Enrollment in last school year t-1	0.94	0.24	0.00	1.00	7,627
Attainment (highest)	4.14	3.50	0.00	16.00	7,627
Math score	19.31	3.38	0.00	21.00	4,546
Nepal					
Enrollment in this school year t	0.91	0.29	0.00	1.00	7,823
Enrollment in last school year t-1	0.90	0.31	0.00	1.00	7,823
Attainment (highest)	3.94	3.38	0.00	12.00	7,821
Math score	15.96	6.49	0.00	21.00	4,617
Pakistan					
Enrollment in this school year t	0.68	0.47	0.00	1.00	71,064
Enrollment in last school year t-1	0.63	0.48	0.00	1.00	71,050
Attainment (highest)	2.77	3.37	0.00	13.00	71,027
Math score (total)	10.09	7.43	0.00	21.00	36,006
Thailand					
Enrollment in this school year t	0.98	0.13	0.00	1.00	9,607
Enrollment in last school year t-1	0.98	0.15	0.00	1.00	9,606
Attainment (highest)	2.78	2.60	0.00	9.00	9,597
Math score	19.57	3.27	0.00	21.00	6,704
Turkmenistan					
Enrollment in this school year t	0.91	0.29	0.00	1.00	3,775
Enrollment in last school year t-1	0.87	0.34	0.00	1.00	3,775
Attainment (highest)	4.02	3.35	0.00	12.00	3,775
Math score	20.11	1.97	0.00	21.00	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 4: Summary statistics for disaster experience by country

Children who had any disaster (DB^A) ...	Mean	SD	Min	Max	N
Bangladesh					
Survey month	0.08	0.27	0.00	1.00	40,617
Year prior to survey month	0.68	0.46	0.00	1.00	40,617
First 1,000 days of life	0.75	0.44	0.00	1.00	40,617
Mid-child life	0.74	0.44	0.00	1.00	40,617
Kyrgyz Republic					
Survey month	0.00	0.00	0.00	0.00	3,897
Year prior to survey month	0.00	0.00	0.00	0.00	3,897
First 1,000 days of life	0.46	0.50	0.00	1.00	3,897
Mid-child life	0.66	0.47	0.00	1.00	3,897
Mongolia					
Survey month	0.32	0.47	0.00	1.00	7,628
Year prior to survey month	0.86	0.35	0.00	1.00	7,628
First 1,000 days of life	0.52	0.50	0.00	1.00	7,628
Mid-child life	0.77	0.42	0.00	1.00	7,628
Nepal					
Survey month	0.00	0.00	0.00	0.00	7,824
Year prior to survey month	0.19	0.39	0.00	1.00	7,824
First 1,000 days of life	0.31	0.46	0.00	1.00	7,824
Mid-child life	0.52	0.50	0.00	1.00	7,824
Pakistan					
Survey month	0.08	0.27	0.00	1.00	71,121
Year prior to survey month	0.62	0.49	0.00	1.00	71,121
First 1,000 days of life	0.54	0.50	0.00	1.00	71,121
Mid-child life	0.69	0.46	0.00	1.00	71,121
Thailand					
Survey month	0.04	0.21	0.00	1.00	9,608
Year prior to survey month	0.03	0.18	0.00	1.00	9,608
First 1,000 days of life	0.68	0.47	0.00	1.00	9,608
Mid-child life	0.87	0.34	0.00	1.00	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. DB^A is an indicator that is equal to one if there is any type of disaster in the designated time span and zero if not. For example, DB^A being equal to one in a survey month means there was a disaster in the month when the child was surveyed. 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 5: Effects of disasters on enrollments

	(1) All disasters	(2) Flood	(3) Severe disasters	(4) Severe flood
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 type A as all disasters, B as only floods, and C as severe disasters, which are defined as causing more than 500 casualties or affecting at least 5,000 people. Type D combines B and C, considering 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.

Table 6: 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
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 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 type A as all disasters, B as only floods, and C as severe disasters, which are defined as causing more than 500 casualties or affecting at least 5,000 people. Type D combines B and C, considering 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.

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

	(1) All disasters	(2) Flood	(3) Severe disasters	(4) Severe flood
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 type A as all disasters, B as only floods, and C as severe disasters, which are defined as causing more than 500 casualties or affecting at least 5,000 people. Type D combines B and C, considering 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.

Table 8: Effects of disasters on math scores

	(1) All disasters	(2) Flood	(3) Severe disasters	(4) Severe flood
***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*				
(> 1,000 days) & (< 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 7. For the disaster intensity type, we consider type A as all disasters, B as only floods, and C as severe disasters, which are defined as causing more than 500 casualties or affecting at least 5,000 people. Type D combines B and C, considering 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.

Table 9: 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
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 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 7. For the disaster intensity type, we consider type A as all disasters, B as only floods, and C as severe disasters, which are defined as causing more than 500 casualties or affecting at least 5,000 people. Type D combines B and C, considering 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.

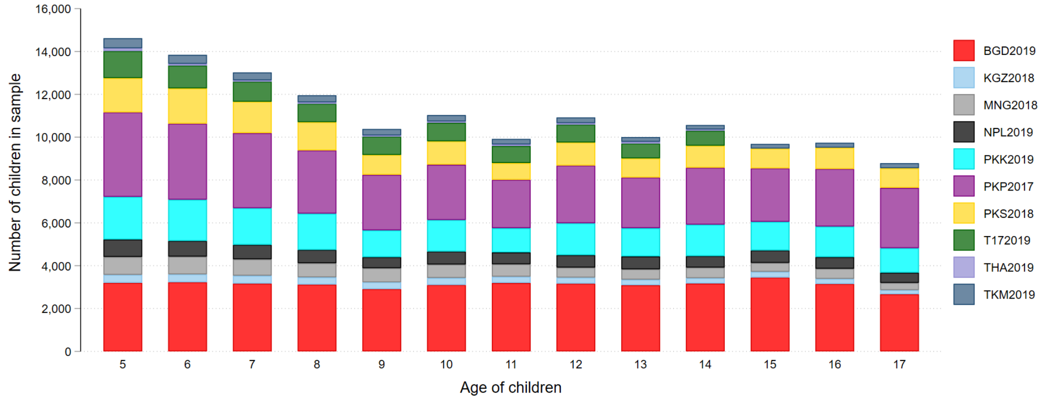
Table 10: Disasters and math scores, heterogeneity across gender and age groups

	(1) All disasters	(2) Flood	(3) Severe disasters	(4) Severe flood
# 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

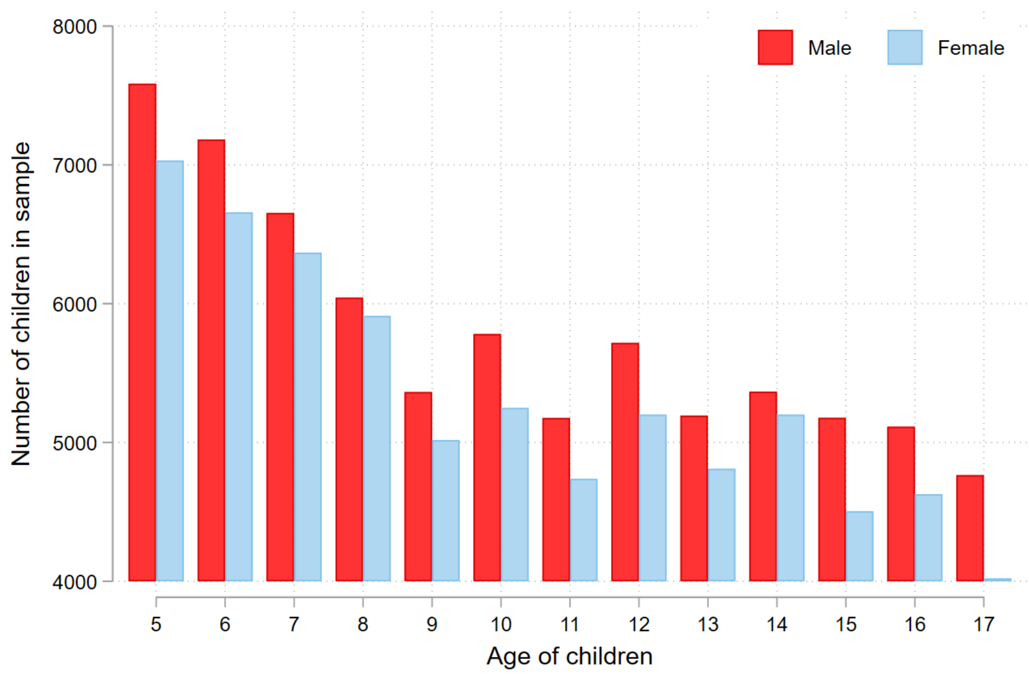
Note: This table shows heterogeneity analyses across gender and ages for disaster effects on math-test scores. This corresponds to Eq. (3), with interacting disaster shocks between age groups and gender. The first 1,000 days is defined as the period from conception to 24 months of age in child development; 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 7. For the disaster intensity type, we consider type A as all disasters, B as only floods, and C as severe disasters, which are defined as causing more than 500 casualties or affecting at least 5,000 people. Type D combines B and C, considering 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.

Figure 1: Sample Size Across Countries, Ages, and Gender

(a) Sample Size Across Countries and Ages



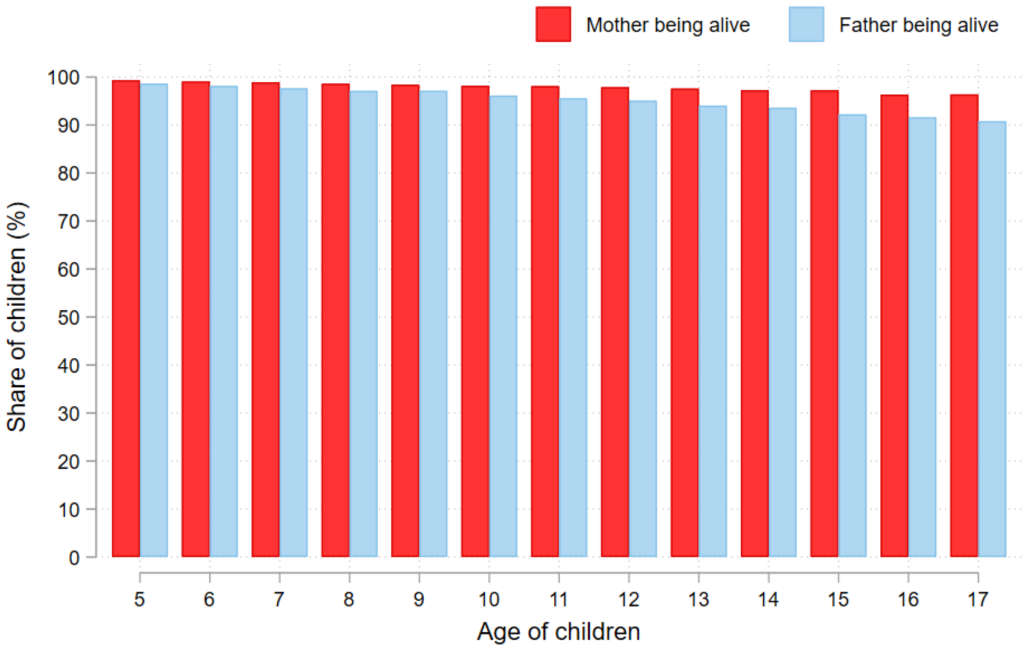
(b) Sample Size Across Gender and Ages



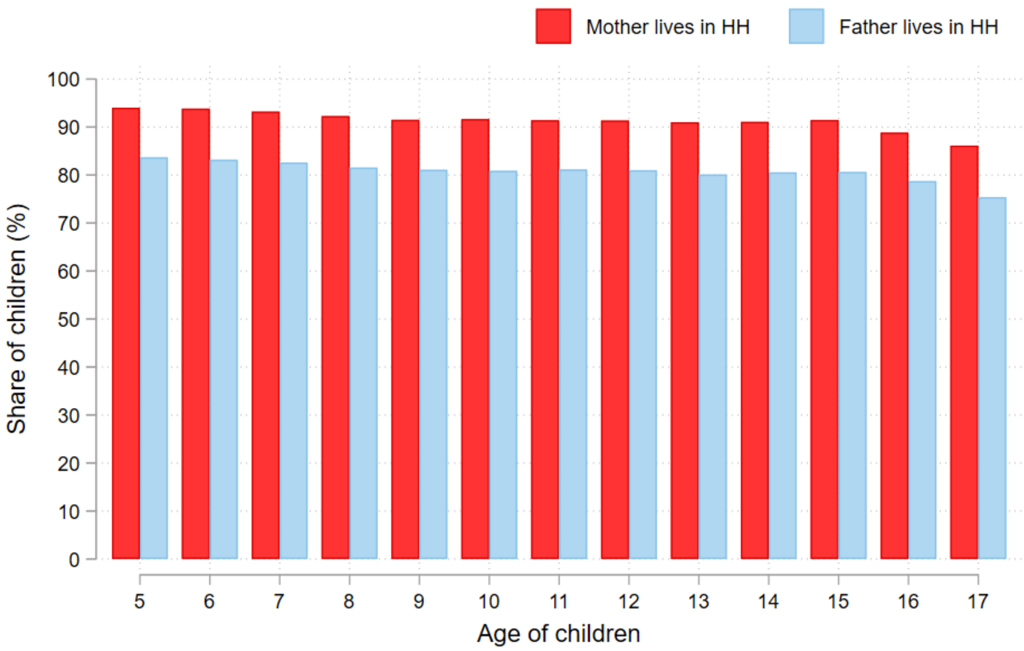
Note: Panel (a) shows the number of children for each age and country. There are 144,471 children in the full sample, dominated by Bangladesh and Pakistan. For every age and country, there are more boys interviewed than girls. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), 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 2: Parental Presence by Children's Age

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



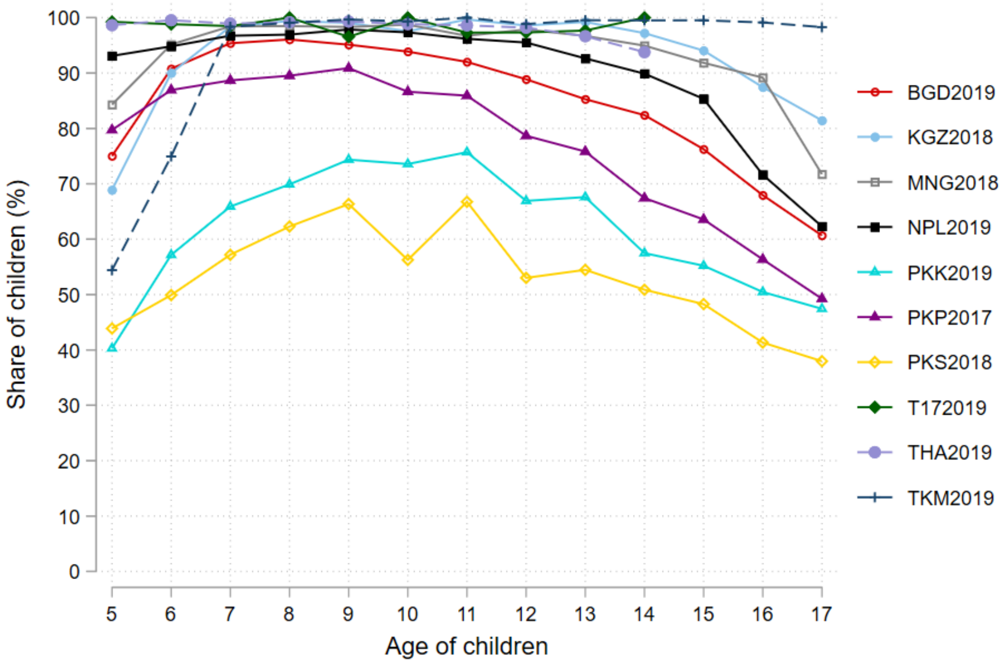
(b) Share of Children Living with Mother or Father by Age



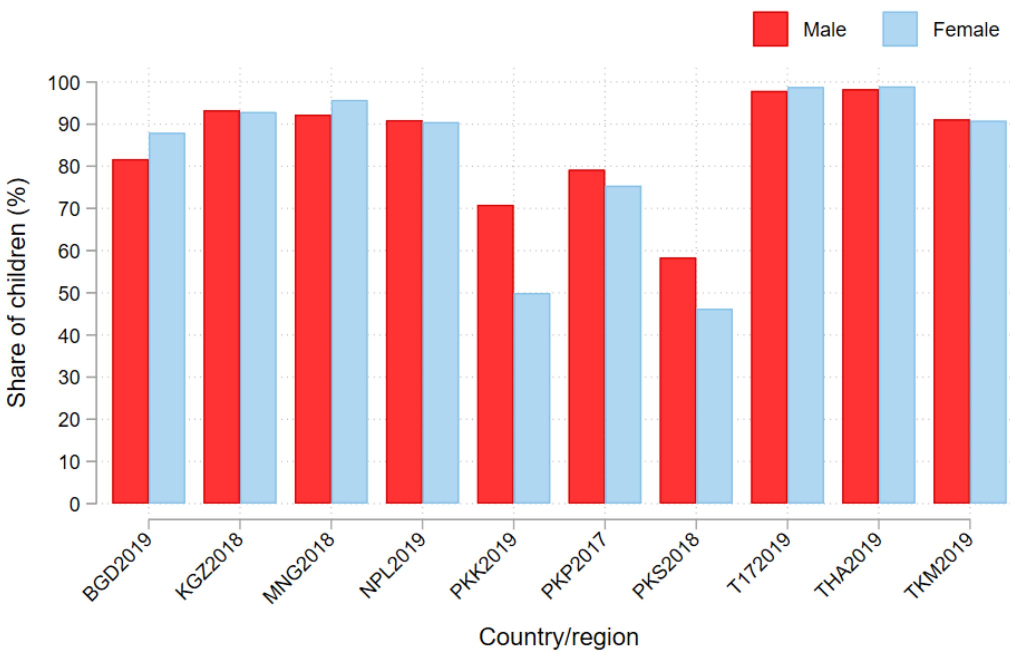
Note: Panel (a) shows the share of children with a mother or father who is alive by child age. Panel (b) shows the share of children living with either their mother or father by age.

Figure 3: Enrollment Fraction in Survey Year

(a) Enrollment Fraction in Survey Year by Age and Country



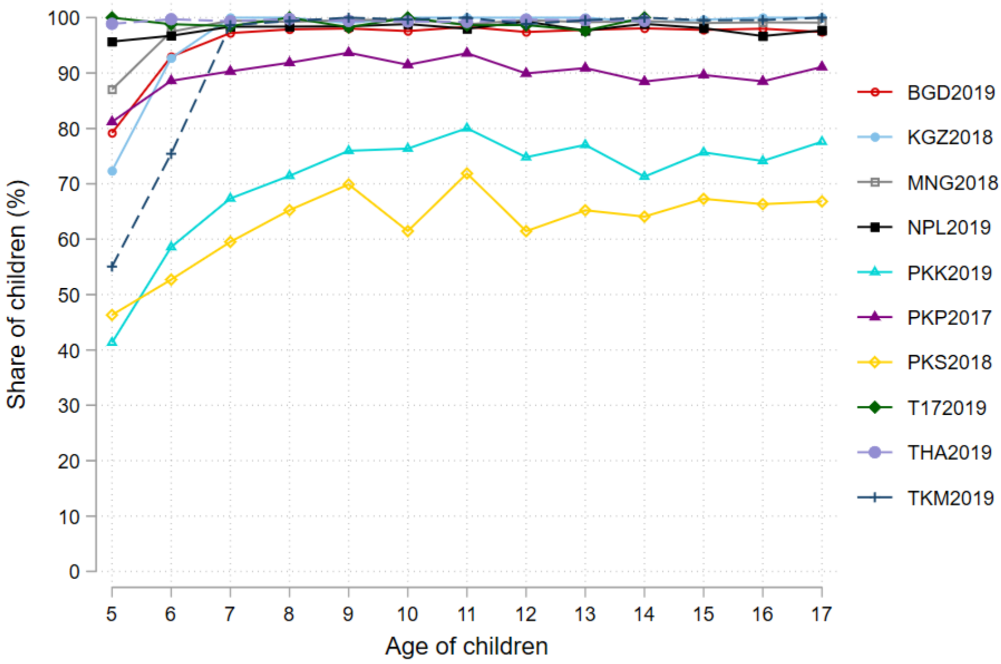
(b) Enrollment Fraction in Survey Year by Gender and Country



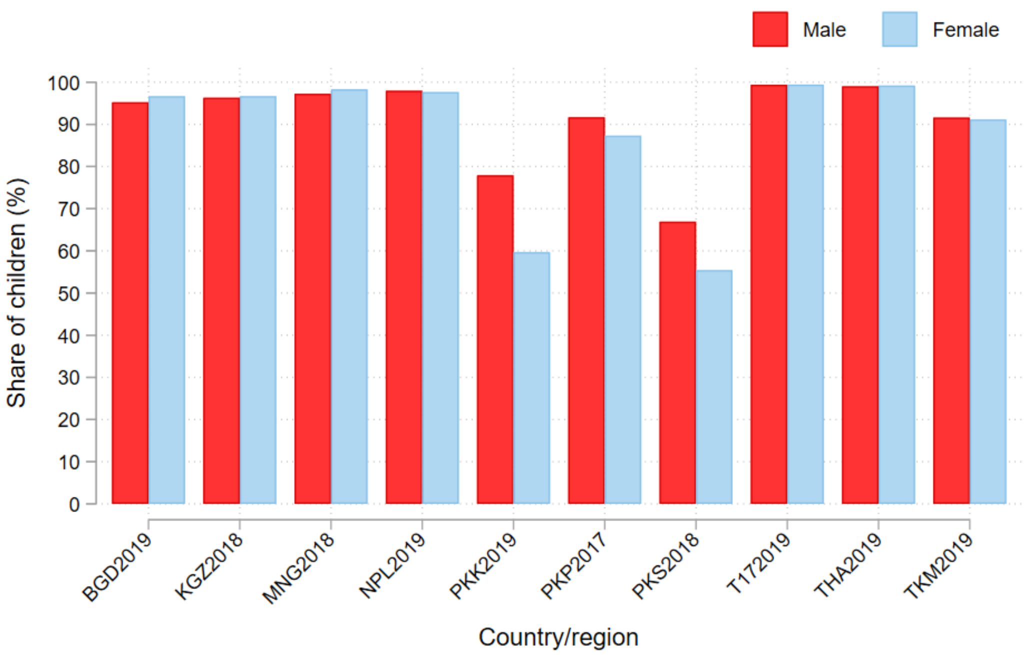
Note: Enrollment fraction in survey year. In Thailand, data are observed only up to age 14; in all other countries, data are available up to age 17. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** 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 4: Share of Children Ever Enrolled in School

(a) Share of Children Ever Enrolled in School by Age and Country



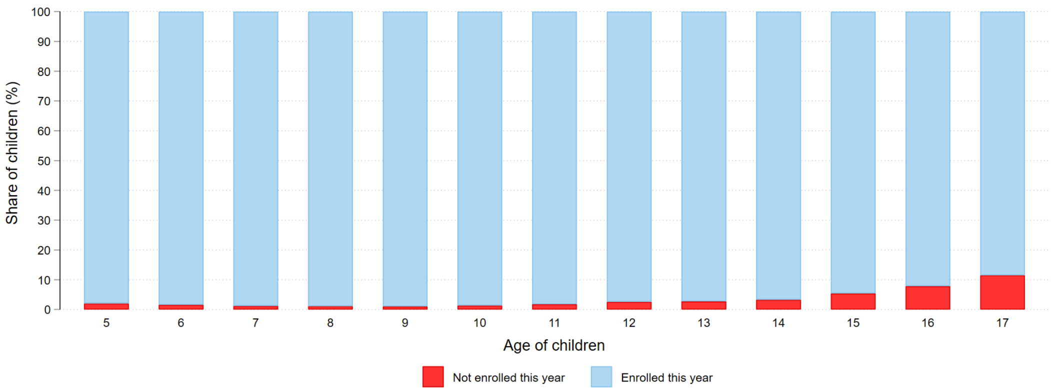
(b) Share of Children Ever Enrolled in School by Gender and Country



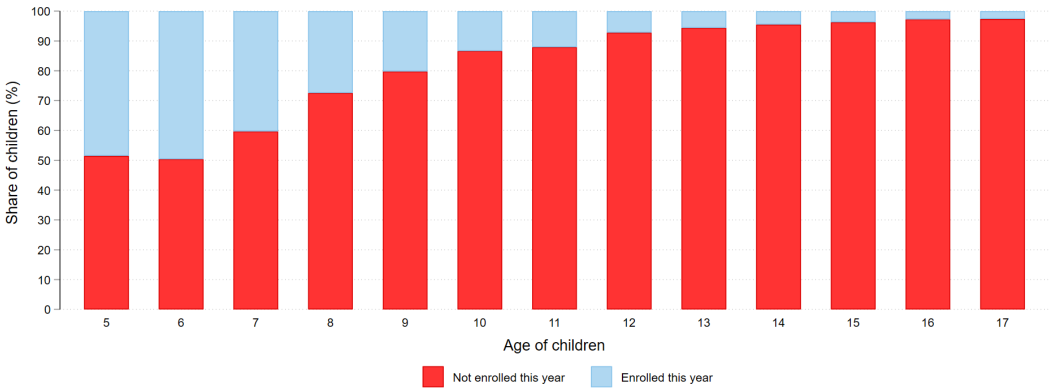
Note: The survey asks if a child has ever been enrolled in school. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only), the Kyrgyz Republic (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure 5: Enrollment Transition Probabilities by Age

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



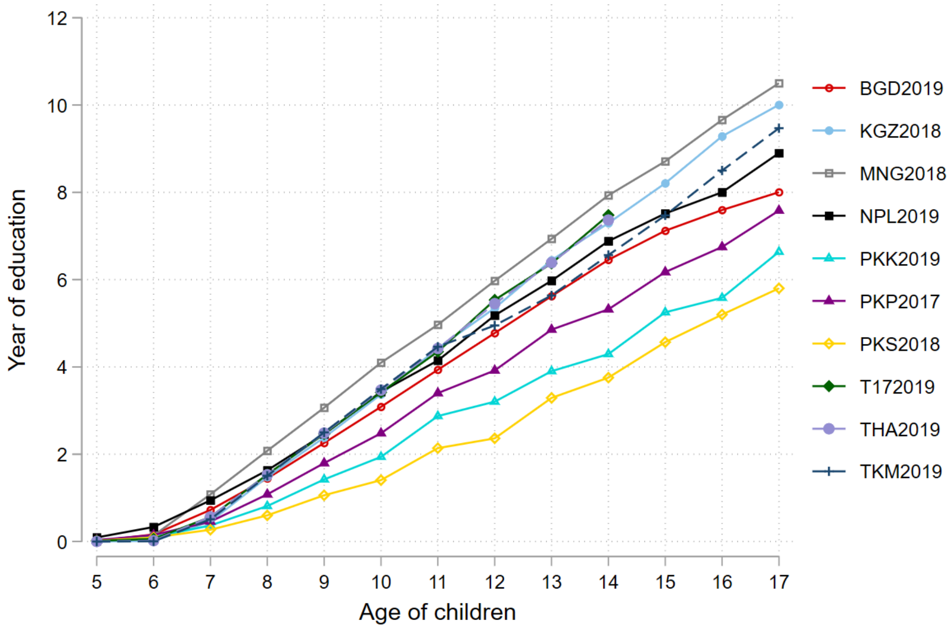
(b) Enrollment Fraction in Survey Year Conditional on **Not Being Enrolled** in the Previous Year



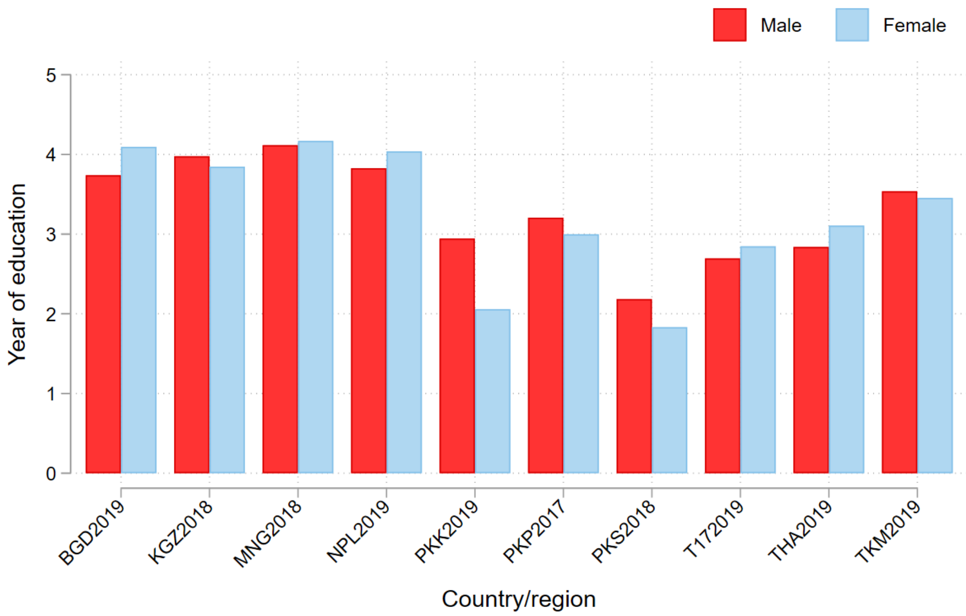
Note: Enrollment fraction in survey year conditional on being **enrolled** the previous year. The results show conditional probabilities.

Figure 6: Average Grades of Schooling Completed by Age and Country

(a) Average Grades of Schooling Completed by Age and Country



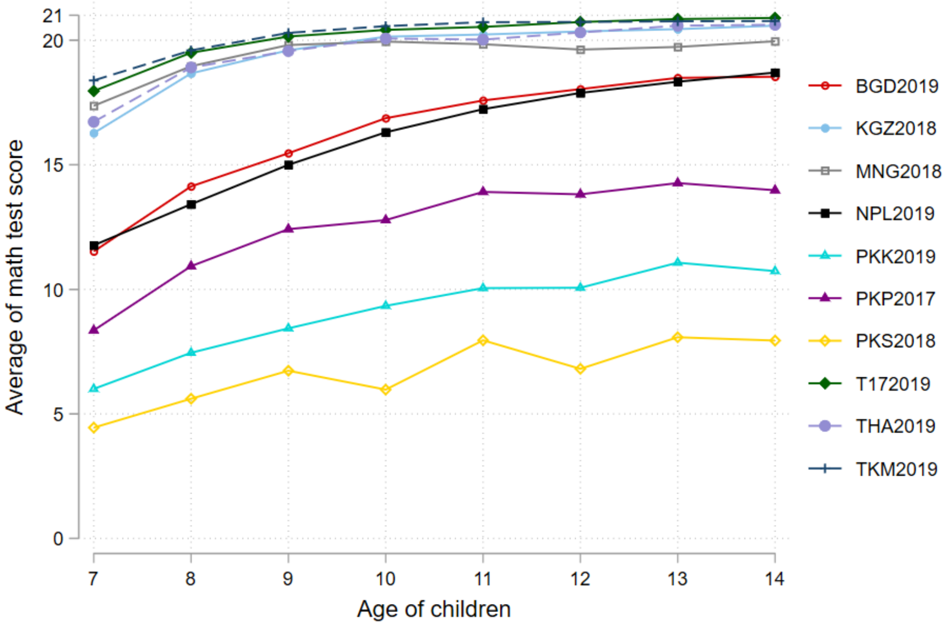
(b) Average Grades of Schooling Completed by Gender and Country



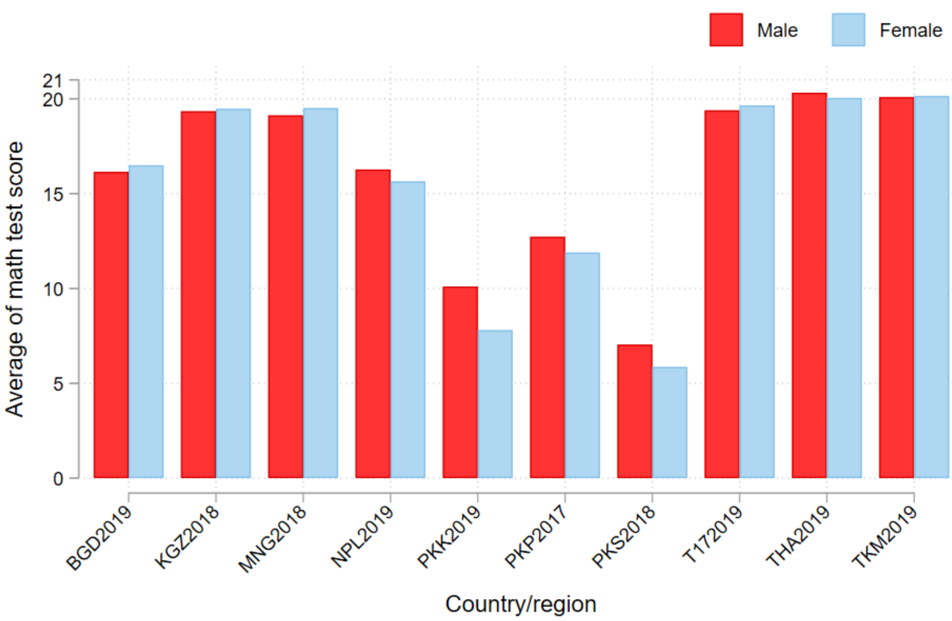
Note: In Thailand, data are observed only up to age 14; in all other countries, data are available up to age 17. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), 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 education level and grade, as well as the country-specific education 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 education completed at the start of this school year.

Figure 7: Distribution of Math Scores

(a) Average of Math Scores by Age and Country

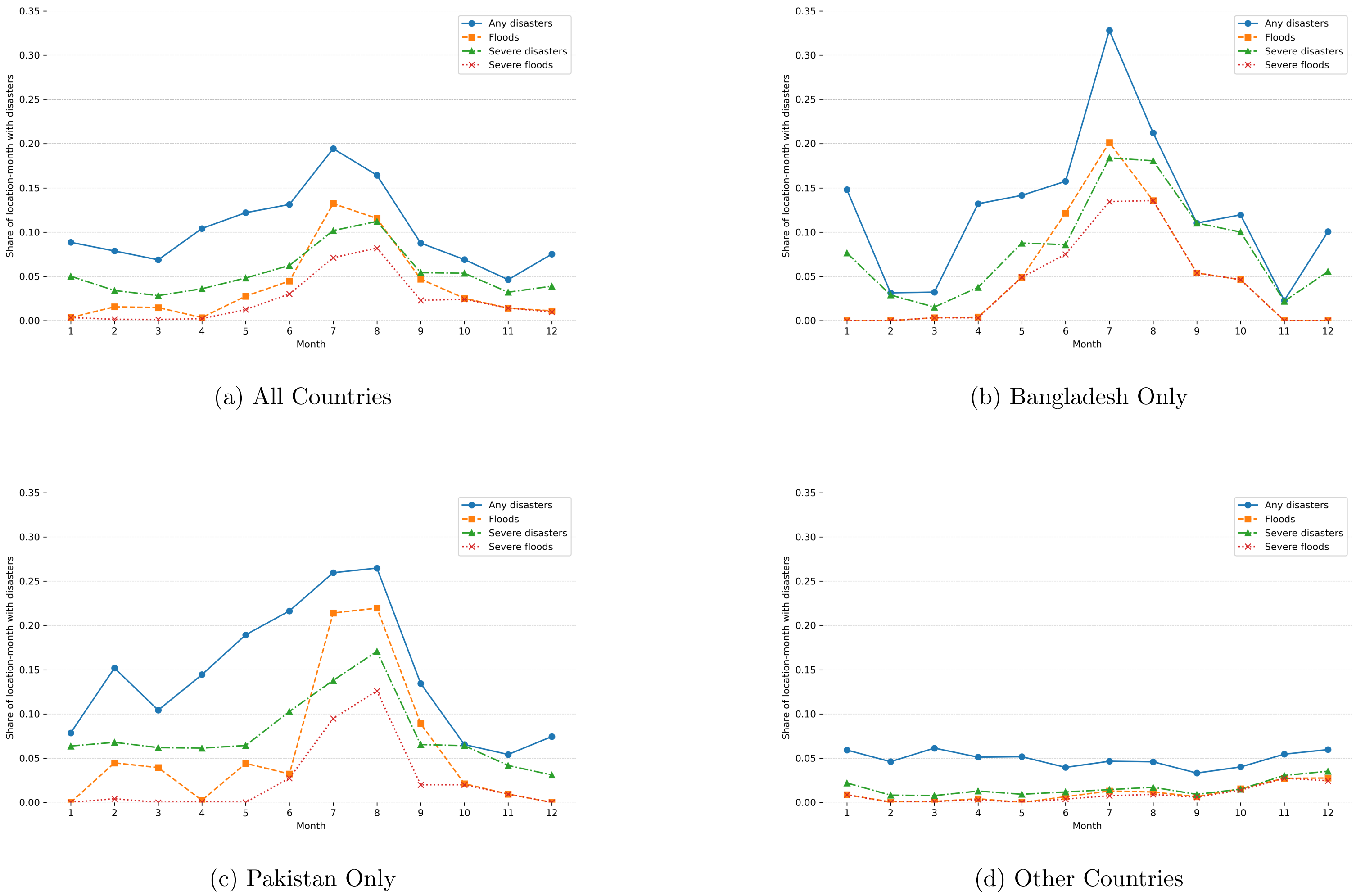


(b) Average of Math Scores by Gender and Country (Ages 7–14)



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 8: 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.

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ONLINE APPENDIX

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

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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 education 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.

Figures 3 and 4 present the distribution of E_t and E_{ever} by age and country. Jointly considering E_t and E_{t-1}, Figure 5 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 6 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.2); hence, our analysis in the main text focuses on math scores, which are much more widely available (see Appendix Figure C.1). 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.7 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 7 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

Appendix Tables C.1 and C.2 present summary statistics on child age, child gender, parental age, 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' Age and Education

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. We obtain the mother's and father's birth years and months from question HL5 and use question HL6 to confirm their ages.

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.3 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. Figure 2 presents the shares of children with parental loss and co-residing parents. Appendix Figure C.4 presents the maternal and paternal joint loss status by country and age. Appendix Figure C.5 presents the mother-child and father-child joint co-residence status by country and age.

B Climate Data (EM-DAT) Appendix (Online)

B.1 The 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.2.3 Illustrative Example

We now use disaster "2016-0375-PAK" as an illustrative example. From the "origin" variable, we know this was a flash flood event that resulted from heavy rain. 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)." The "GeoLocations" variable augments the "location" variable with information on which within-country administrative level the location name falls under. Not all disaster inputs have "GeoLocations".[B.1] When available, we use the "GeoLocations" information to match location names to corresponding administrative-level locations where MICS6 children reside. When "GeoLocations" is unavailable, we match after searching through the"location" variable names across location names across administrative levels.

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

C Additional Figures and Tables (Online)

This Appendix section provides additional tables and figures. We present additional summary statistics on children and parental characteristics in Tables C.1 and C.2. Table C.3 presents migratory history summary statistics for the mothers of the children. Figures C.1 and C.2 present the shares of the sample reporting math and reading test scores, respectively. Figures C.3, C.4, and C.5 plot parental and household characteristics. The distributions of progression and reading test scores are presented in Figures C.6 and C.7, respectively.

This section also includes supplementary regression results. Table C.4 shows results with fewer controls for the effects of "all disasters" (Type A) on enrollments. Table C.5 shows results for the effects of disaster exposures on enrollments with various disaster exposure measures. Table C.6 presents a heterogeneity analysis for the effects of disaster exposures on enrollments by age and country groups. For the math score outcome, Table C.7 shows results using different measures for disaster exposures, while Table C.8 shows additional results for heterogeneous effects by age and country groups.

Table C.1: Summary statistics for child and parent attributes by country

	Mean	SD	Min	Max	N
Bangladesh					
Age of child	10.95	3.72	5.00	17.00	40,617
Female	0.48	0.50	0.00	1.00	40,617
Mother's age	35.88	8.24	2.00	80.00	37,494
Father's age	43.66	9.75	7.00	95.00	33,485
Kyrgyz Republic					
Age of child	10.34	3.67	5.00	17.00	3,897
Female	0.47	0.50	0.00	1.00	3,897
Mother's age	38.52	8.24	21.00	76.00	3,303
Father's age	42.19	8.31	24.00	86.00	2,908
Mongolia					
Age of child	10.06	3.67	5.00	17.00	7,628
Female	0.49	0.50	0.00	1.00	7,628
Mother's age	37.66	7.28	20.00	77.00	6,612
Father's age	39.40	7.70	20.00	84.00	5,592
Nepal					
Age of child	10.55	3.80	4.00	17.00	7,824
Female	0.50	0.50	0.00	1.00	7,824
Mother's age	35.91	8.64	13.00	95.00	7,083
Father's age	40.32	9.66	0.00	95.00	5,240
Pakistan					
Age of child	10.49	3.87	5.00	17.00	71,121
Female	0.48	0.50	0.00	1.00	71,121
Mother's age	39.09	9.00	18.00	95.00	67,435
Father's age	43.77	9.93	18.00	95.00	60,983
Thailand					
Age of child	9.03	2.91	5.00	14.00	9,608
Female	0.48	0.50	0.00	1.00	9,608
Mother's age	37.02	7.40	18.00	61.00	6,632
Father's age	40.67	8.20	19.00	80.00	5,351
Turkmenistan					
Age of child	10.08	3.81	5.00	17.00	3,776
Female	0.48	0.50	0.00	1.00	3,776
Mother's age	37.51	7.33	22.00	95.00	3,584
Father's age	38.96	7.39	23.00	77.00	3,232

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.2: Summary statistics for parental education and co-residency with children by country

	Mean	SD	Min	Max	N
Bangladesh					
Mother ever educated	0.74	0.44	0.00	1.00	40,587
Mother has secondary sch. education	0.46	0.50	0.00	1.00	40,587
Father ever educated	0.67	0.47	0.00	1.00	33,468
Mother is living in same HH	0.92	0.27	0.00	1.00	40,603
Father is living in same HH	0.83	0.38	0.00	1.00	40,581
Kyrgyz Republic					
Mother ever educated	0.99	0.09	0.00	1.00	3,897
Mother has secondary sch. education	0.92	0.27	0.00	1.00	3,897
Father ever educated	1.00	0.05	0.00	1.00	2,908
Mother is living in same HH	0.85	0.36	0.00	1.00	3,888
Father is living in same HH	0.75	0.43	0.00	1.00	3,879
Mongolia					
Mother ever educated	0.94	0.25	0.00	1.00	7,595
Mother has secondary sch. education	0.64	0.48	0.00	1.00	7,595
Father ever educated	0.90	0.30	0.00	1.00	5,588
Mother is living in same HH	0.87	0.34	0.00	1.00	7,622
Father is living in same HH	0.74	0.44	0.00	1.00	7,529
Nepal					
Mother ever educated	0.52	0.50	0.00	1.00	7,821
Mother has secondary sch. education	0.24	0.43	0.00	1.00	7,821
Father ever educated	0.76	0.43	0.00	1.00	5,237
Mother is living in same HH	0.91	0.29	0.00	1.00	7,821
Father is living in same HH	0.67	0.47	0.00	1.00	7,814
Pakistan					
Mother ever educated	0.36	0.48	0.00	1.00	71,059
Mother has secondary sch. education	0.16	0.36	0.00	1.00	71,059
Father ever educated	0.61	0.49	0.00	1.00	60,991
Mother is living in same HH	0.95	0.22	0.00	1.00	70,945
Father is living in same HH	0.86	0.35	0.00	1.00	71,020
Thailand					
Mother ever educated	0.95	0.21	0.00	1.00	9,603
Mother has secondary sch. education	0.36	0.48	0.00	1.00	9,603
Father ever educated	0.97	0.18	0.00	1.00	5,344
Mother is living in same HH	0.69	0.46	0.00	1.00	9,573
Father is living in same HH	0.56	0.50	0.00	1.00	9,482
Turkmenistan					
Mother ever educated	1.00	0.02	0.00	1.00	3,776
Mother has secondary sch. education	0.25	0.43	0.00	1.00	3,776
Father ever educated	1.00	0.03	0.00	1.00	3,232
Mother is living in same HH	0.95	0.22	0.00	1.00	3,770
Father is living in same HH	0.86	0.35	0.00	1.00	3,763

Note: This table shows summary statistics for some more demographic characteristics by country.

Table C.3: Summary statistics for residential duration by country

	Percentiles 5th	10th	15th	20th	Mean	SD	Obs
Bangladesh							
Residential duration exceeds age	0.00	0.00	1.00	1.00	0.89	0.32	33674
Ratio of residential duration to age	0.43	0.88	1.00	1.00	0.94	0.19	33674
Kyrgyz Republic							
Residential duration exceeds age	0.00	0.00	1.00	1.00	0.86	0.35	2926
Ratio of residential duration to age	0.36	0.71	1.00	1.00	0.93	0.21	2926
Mongolia							
Residential duration exceeds age	0.00	0.00	0.00	1.00	0.83	0.38	5883
Ratio of residential duration to age	0.38	0.67	0.88	1.00	0.92	0.20	5883
Nepal							
Residential duration exceeds age	0.00	0.00	0.00	1.00	0.85	0.36	6401
Ratio of residential duration to age	0.35	0.67	0.94	1.00	0.93	0.21	6401
Pakistan							
Residential duration exceeds age	0.00	0.00	1.00	1.00	0.89	0.32	40143
Ratio of residential duration to age	0.33	0.83	1.00	1.00	0.93	0.21	40143
Thailand							
Residential duration exceeds age	0.00	0.00	1.00	1.00	0.86	0.35	6157
Ratio of residential duration to age	0.38	0.73	1.00	1.00	0.93	0.20	6157
Turkmenistan							
Residential duration exceeds age	1.00	1.00	1.00	1.00	0.96	0.20	3335
Ratio of residential duration to age	1.00	1.00	1.00	1.00	0.98	0.11	3335

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.4: 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.

Table C.5: Effects of disasters on enrollments using different disaster measures

	(1)	(2)	(3)	(4)
		Had disaster in		# of mo. with disaster in
	survey mo.	most recent 3 mo.	most recent 12 mo.	most recent 12 mo.
Recent disaster experience	0.006	0.003	−0.004	0.003
	(0.005)	(0.005)	(0.006)	(0.003)
# of mo. with disaster in the first 1,000 days	−0.001**	−0.001**	−0.001**	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Enrollment in year $t-1$	0.388***	0.388***	0.388***	0.388***
	(0.012)	(0.012)	(0.012)	(0.012)
Attainment at start of t	0.012***	0.012***	0.012***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
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 × has secondary education	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	143645	143645	143645	143645
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 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.

Table C.6: Disasters and enrollments, heterogeneity across age groups and countries

	(1)
Had disaster in most recent 12 mo.	
× Pakistan	
× Age 5–8	−0.105*
	(0.056)
× Age 9–12	−0.110**
	(0.055)
× Age 13–17	−0.101*
	(0.058)
× Bangladesh	
× Age 5–8	0.044***
	(0.014)
× Age 9–12	−0.011
	(0.008)
× Age 13–17	−0.027**
	(0.012)
× Other countries	
× 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	
× Age 5–8	−0.006**
	(0.003)
× Age 9–12	−0.001
	(0.001)
× Age 13–17	−0.001
	(0.002)
× Bangladesh	
× Age 5–8	0.003
	(0.002)
× Age 9–12	−0.002**
	(0.001)
× Age 13–17	−0.003***
	(0.001)
× Other countries	
× Age 5–8	0.002***
	(0.000)
× Age 9–12	−0.000
	(0.000)
× Age 13–17	−0.001
	(0.001)
Observations	143645
Within-country location FE	Y
Interview year FE	Y
Interview month FE	Y
Child age FE	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 a heterogeneous 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.

Table C.7: 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)
Female	-0.417^{***}	-0.419^{***}	-0.419^{***}
	(0.060)	(0.061)	(0.061)
Mother is alive	0.327^{**}	0.325^{**}	0.324^{**}
	(0.160)	(0.160)	(0.160)
Father is alive	0.223^{**}	0.225^{**}	0.225^{**}
	(0.105)	(0.105)	(0.105)
Mother is alive × living in same HH	0.053	0.055	0.056
	(0.080)	(0.080)	(0.080)
Father is alive × living in same HH	-0.215^{***}	-0.215^{***}	-0.216^{***}
	(0.061)	(0.061)	(0.061)
Mother ever educated	1.341^{***}	1.340^{***}	1.340^{***}
	(0.082)	(0.082)	(0.082)
Mother ever educated × has secondary education	0.998^{***}	0.996^{***}	0.996^{***}
	(0.067)	(0.067)	(0.067)
Observations	78305	78305	78305
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
Country × attainment t FE	Y	Y	Y

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.

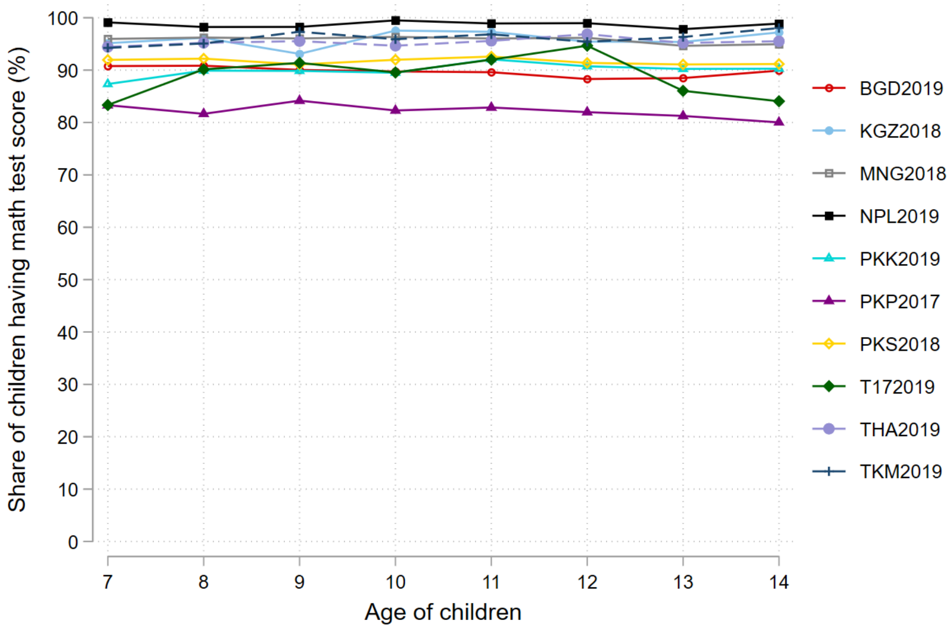
Table C.8: Disasters and math scores, heterogeneity across age groups and countries

	(1)
# of mo. with disaster in mid-child life	
× Pakistan	
× Age 7–9	−0.045
	(0.070)
× Age 10–12	−0.124**
	(0.050)
× Age 13–14	−0.054
	(0.037)
× Bangladesh	
× Age 7–9	−0.153***
	(0.057)
× Age 10–12	−0.030
	(0.030)
× Age 13–14	−0.065**
	(0.029)
× Other countries	
× 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	
× Age 7–9	−0.198***
	(0.065)
× Age 10–12	−0.013
	(0.024)
× Age 13–14	−0.090
	(0.056)
× Bangladesh	
× Age 7–9	0.075
	(0.057)
× Age 10–12	0.038
	(0.032)
× Age 13–14	−0.012
	(0.031)
× Other countries	
× Age 7–9	0.017
	(0.029)
× Age 10–12	0.040
	(0.034)
× Age 13–14	0.086***
	(0.032)
Observations	78303
Within-country location FE	Y
Interview year FE	Y
Interview month FE	Y
Child age FE	Y
Attainment t × country FE	Y

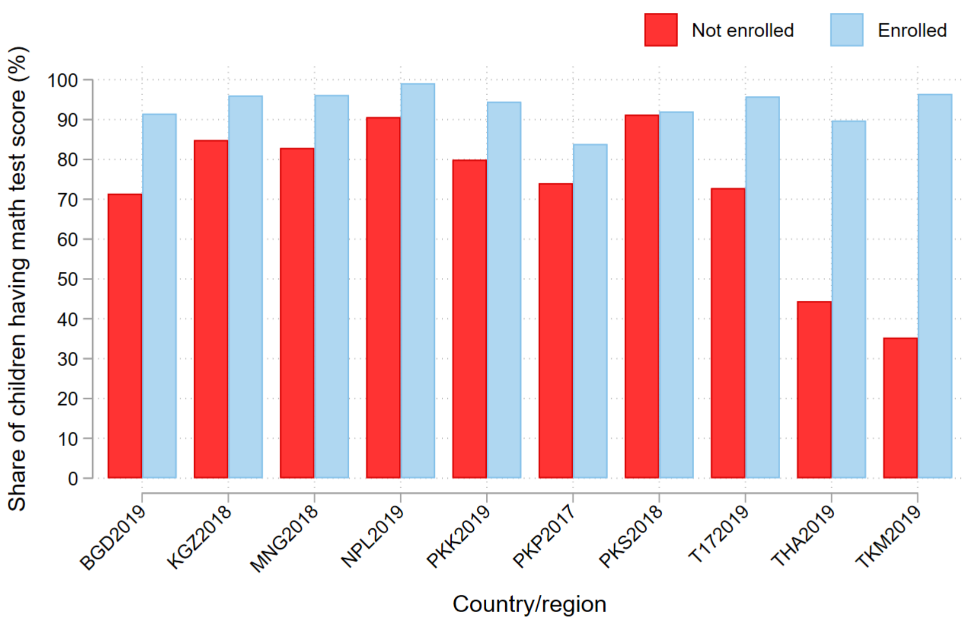
Note: This table shows a heterogeneous analysis across countries and ages of disaster effects on math scores. This corresponds with Eq. (3), with interactions between disaster shocks, age groups, and country groups. Standard errors, clustered at the within-country location level, are reported in parentheses.

Figure C.1: Math Test Sample Size

(a) Math Test Sample Size by Age and Country



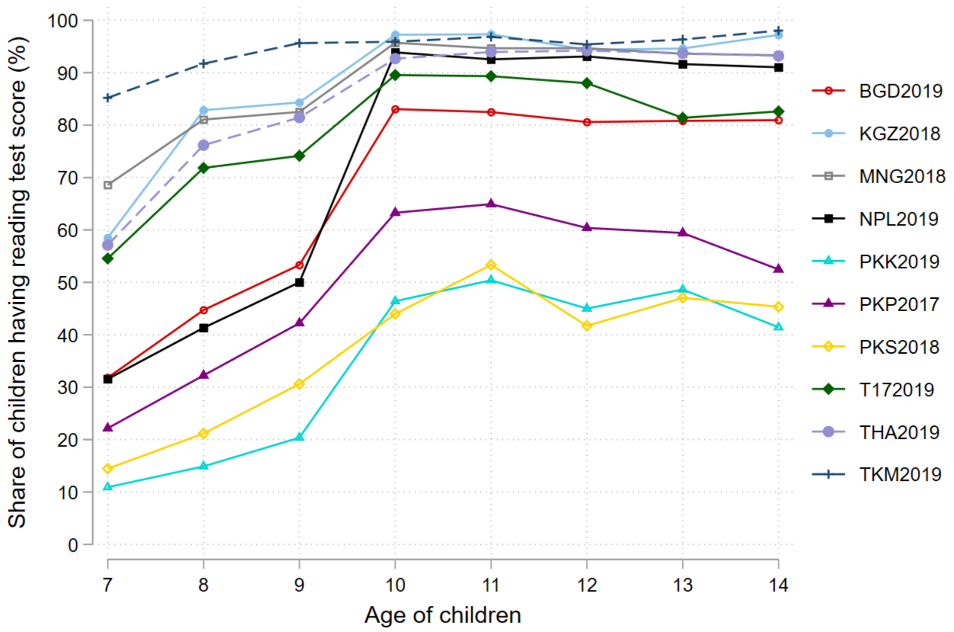
(b) Math Test Sample Size by Enrollment Status in Current Year Across Countries



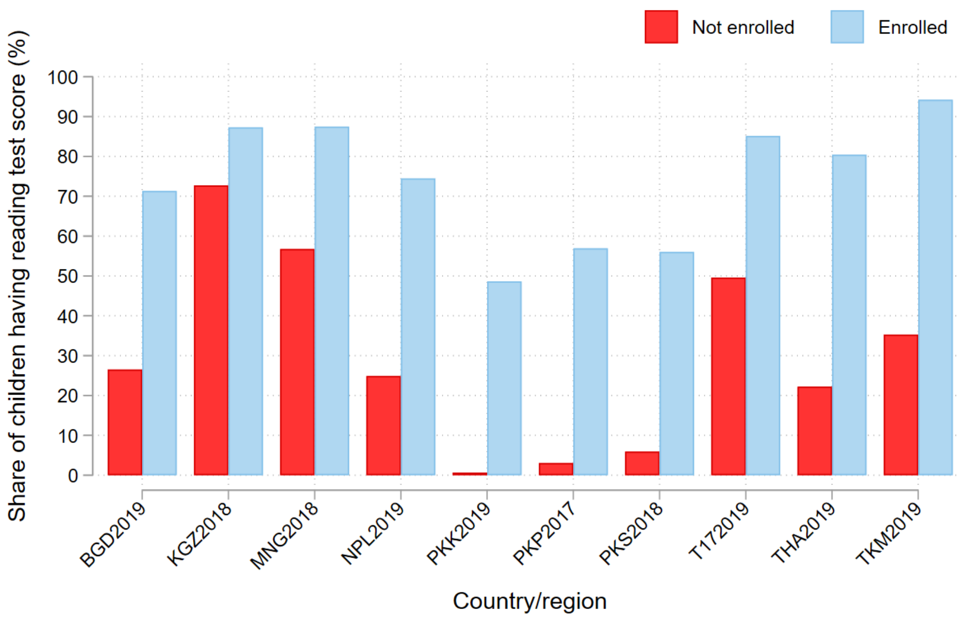
Note: Fractions show the shares of the sample by age and country reporting math scores, with consistent shares across ages and some variation across countries. We find much larger shares with math-test scores reported if the children are enrolled in school; they all exceed an 80% chance. Countries included 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.2: Reading Test Sample Size

(a) Reading Test Sample Size by Age

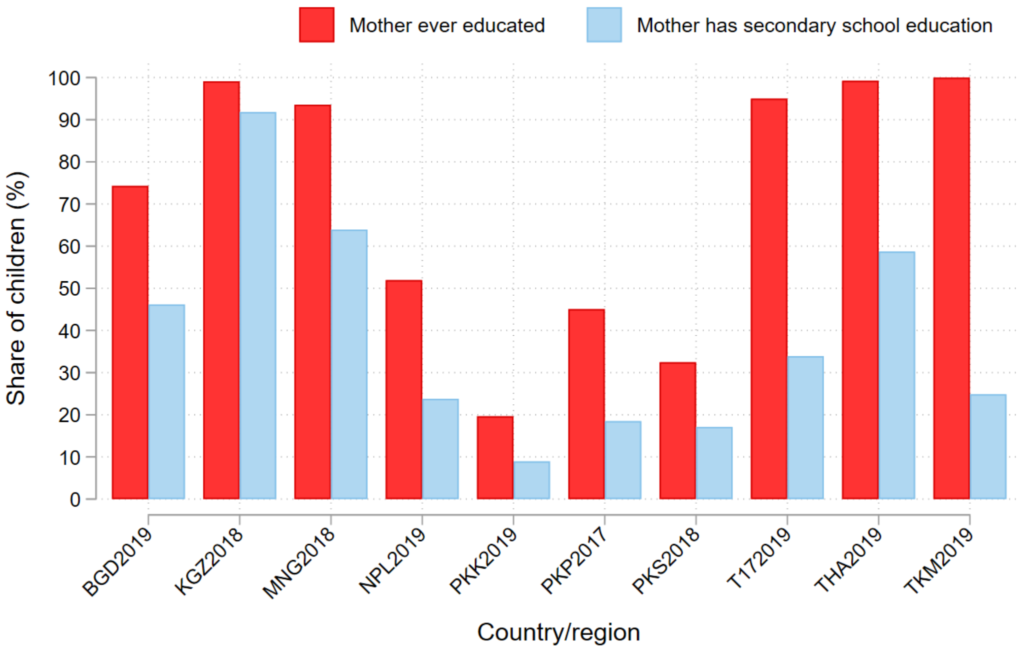


(b) Reading Test Sample Size by Enrollment Status Across Countries



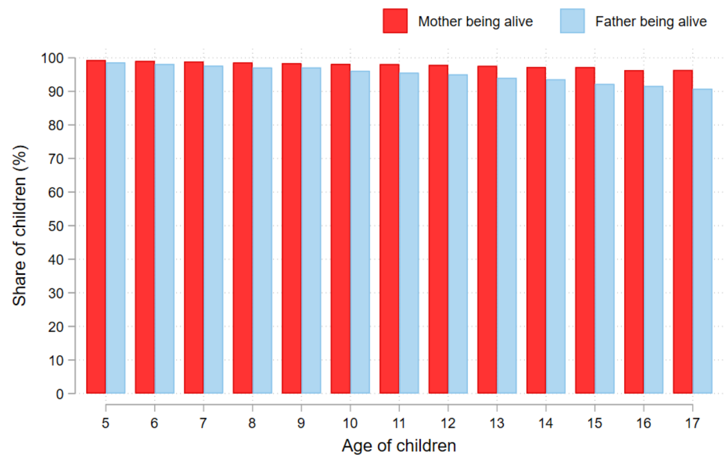
Note: Fractions show the shares of the sample by age and country reporting reading test scores, with consistent shares across ages and some variation across countries. We notice that whether the child has a reading test score is related to if she is enrolled in school in the current period. We find much 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.3: Share of Children Whose Mother Has Some Education

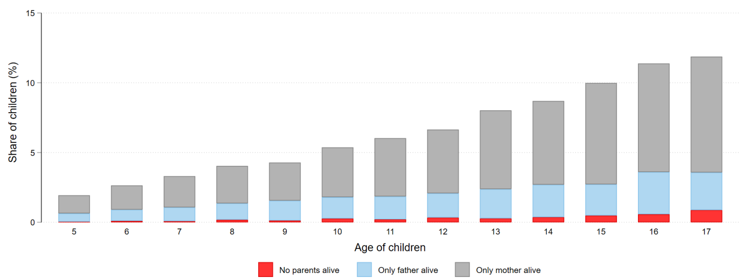


Note: This table shows (1) the share of children whose mother has had any kind of education and (2) the share of children whose mother has secondary school education by country. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **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**).

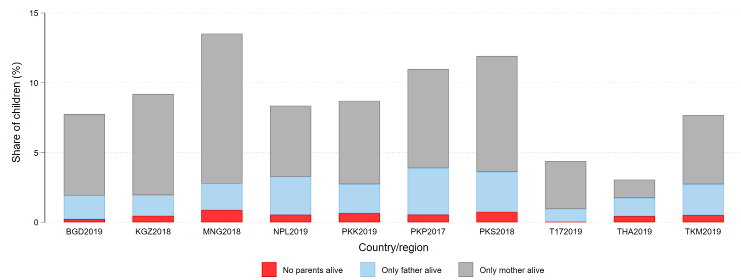
Figure C.4: Share of Children with Mother or Father Alive by Age



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



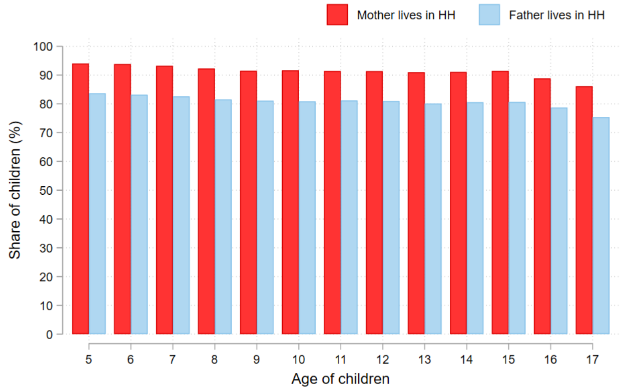
(b) Share of Children with One or Both Parents Alive by Age



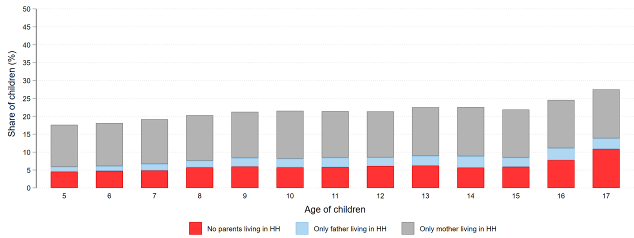
(c) Share of Children (Age ≥ 12) with One or Both Parents Alive by Country

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.

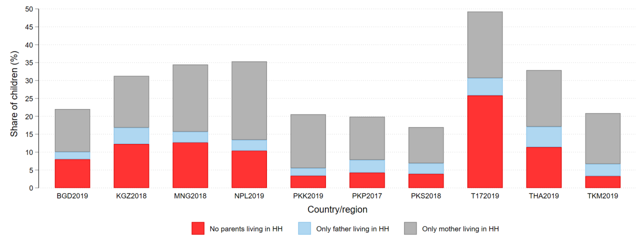
Figure C.5: Share of Children Living with Parents



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



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

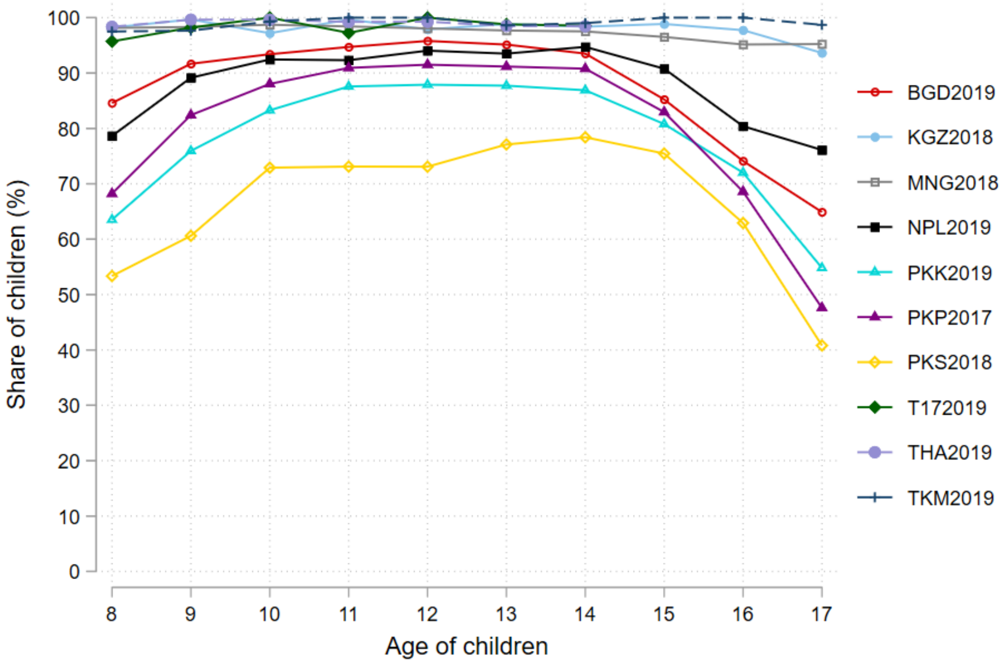


(c) Share of Children (Age $\geq$ 12) Living with One or Both Parents by Country

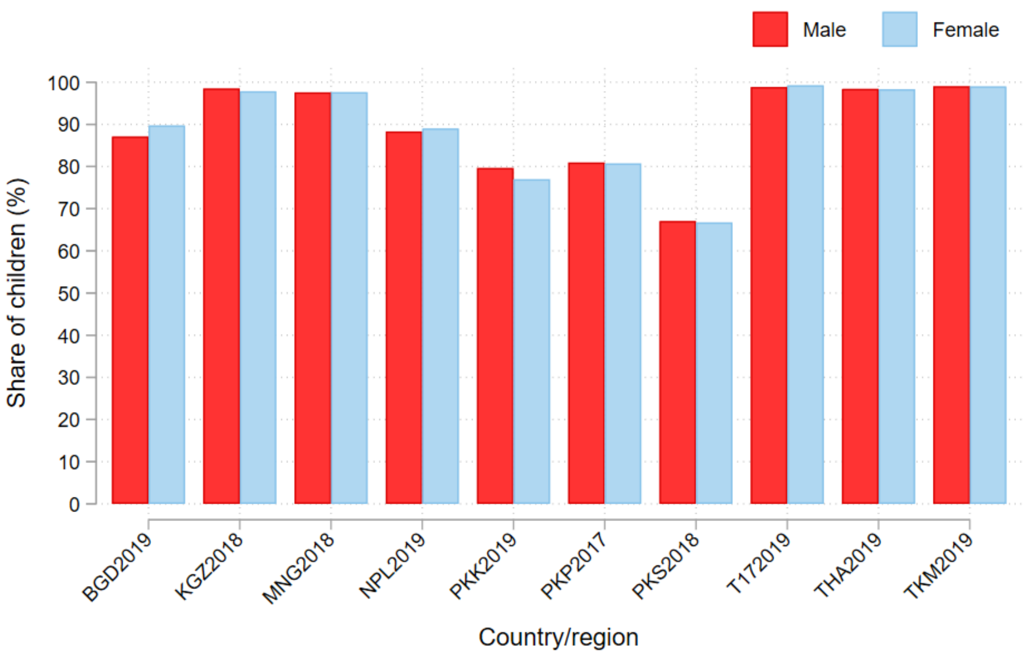
Note: Panel (a) shows the share of children living with either their mother or father by age. Panels (b) and (c) show the share of children living with both parents or one of them by age. The four categories include living with both parents (not included in the bar), living with just the mother, living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

Figure C.6: Distribution of Progression in Last School Year

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



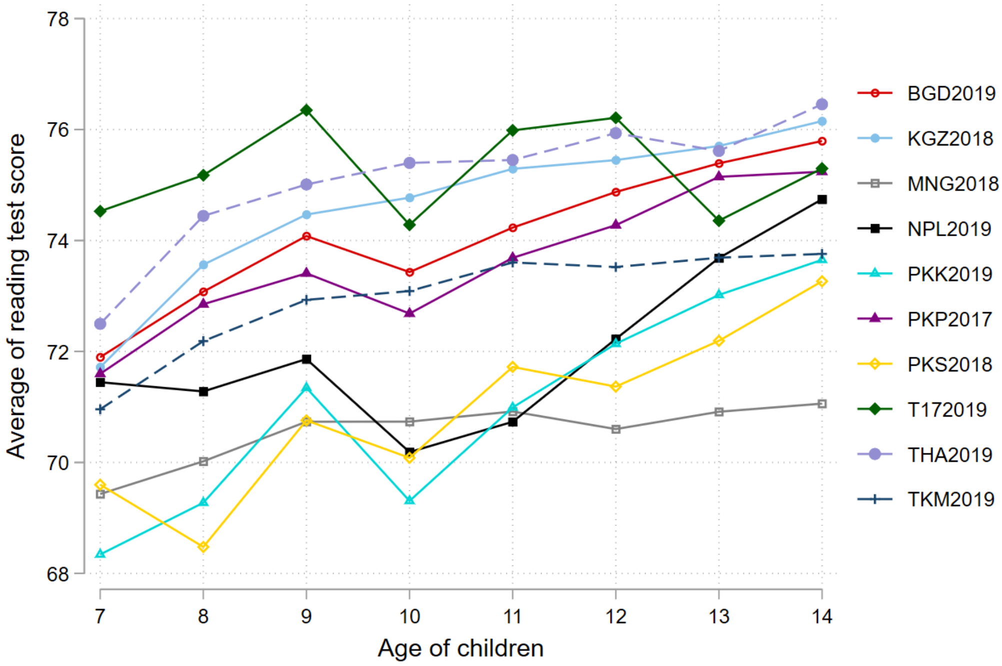
(b) Progression Rate in Last Year by Gender and Country (Age ≥ 8)



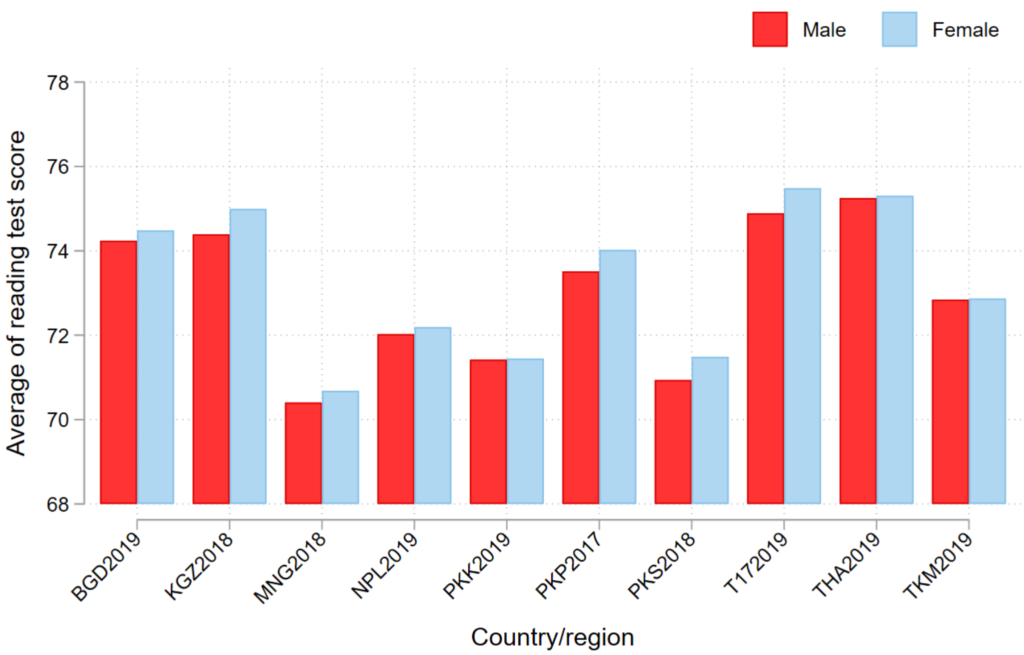
Note: The figure shows progression rates. The progression is equal to 1 if a child attends a grade and successfully completes the grade, leading to an increase in grade completion by 1 year. Countries included are Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber 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.7: 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**).