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 the Asia-Pacific region, 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. 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; variable age patterns of enrollment and learning effects of exposures across countries; and boys' enrollments more negatively affected but girls' math-test scores more negatively affected by early life natural-disaster exposures.

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

JEL: I24, I25, Q54, Q56

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 percent of all disasters, 45 percent of all reported deaths, and 74 percent of all reported economic losses (United Nations 2021). In coming decades, climatic change will continue to lead to 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 the Asia-Pacific region, which is the world's most natural-disaster-prone region (UN-ESCAP 2023). Asia accounts for nearly one third of weather, climatic, and water-related disasters globally, nearly half of all deaths, and one-third of associated economic losses between 1970 and 2019 (United Nations 2021). In 2022, over 140 disasters struck the Asia-Pacific region, causing over 7,500 deaths, affecting over 64 million people, and causing economic damage estimated at US$ 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 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 fewer studies investigate 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 South Korea on college-entrance-exam scores (Cho and Kim 2023), a study showing that lower educational attainment in adulthood came with high-intensity exposure to

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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 human capital both via reductions in learning for students who stay in school and grades completion in school. Simeonova (2011) also uses US data and Currie and Rossin-Slater (2013) study 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 attainments and labor market outcomes in Latin America, as well as the intergenerational transmissions of early life exposures. Our paper in contrast emphasizes educational outcomes of children directly exposed to disasters, examining both enrollments and foundational learning outcomes assessed using MICS-administered math-test scores, which provide a valuable measure of cognitive skills.

the 1976 Tangshan earthquake in China (Tian, Gong, and Zhai 2022), and a study revealing lower cognitive scores in children ages 0-2 who experienced the 2006 Yogyakarta earthquake in Indonesia (Hadiman and Djamaluddin 2022). 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.

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 both schools experiencing disaster-induced damages (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 on households and health shocks on both parents and children. These shocks could cause unanticipated parental deaths, reduce household resource availability for schooling, reduce children's physical capacities 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 enrolment decline if the children in the years of their birth 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 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 ages 5 to 17 from seven developing countries in Asia from the Multiple Indicator Cluster Surveys (MICS) (UNICEF 2010) together with time- and geo-coded disaster variables from the EM-DAT international disaster database (Delforge et al. 2023). Given the countries and ages of children in the sample, we link 355 natural disasters that have led to substantial loss of human life in these countries between 1999 to 2019 from EM-DAT. These disasters include floods, storms, droughts, earthquakes, and extreme temperatures. Exploiting variations in MICS-survey locations, variations in location-specific survey timing, as well as age variations among children surveyed in each location and each month, we develop a novel dataset that provides time-, age- and location-specific disaster

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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. 2021a; UNICEF 2021a). In this paper, we do not study the effects of the COVID-19 pandemic on educational outcomes.

exposure histories for children surveyed in MICS in respective countries.[3]

We investigate the impacts of exposure histories to natural disasters on human-capital accumulation. 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 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 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. This circumstance 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 for 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 for 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 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 as moderated by permanent child- and household-specific factors, we allow for combinations of interactions between natural disasters and 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—

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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).

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 allows us to jointly consider 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, 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 disasters exposures on enrollment status, but weaker or no corresponding effects related to recent-disasters exposures. Heterogeneity analysis shows that there are persistent negative effects of early life natural-disasters 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 current performance on math tests, the negative effects of early life disasters are more persistent for girls than boys in 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 child natural-disasters exposures on educational outcomes probably are underestimated.

These findings contribute to the existing literature showing that the 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 attainments 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 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. Tables and figures that are referenced with a prefix of a capital letter 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 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. 2021b).

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 (Kyrgyzstan 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 organisations, insurance companies, research institutes, and press agencies. A disaster is recorded in EM-DAT if it meets at least one of the following criteria: (a) 10 or more people killed, (b) 100 or more people affected, (c) declaration of a state of emergency, or (d) a call for international assistance (Panwar and Sen 2020; Mavhura and Raj Aryal 2023; Sy et al. 2019).

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5. Foundational math learning is not only 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 due to the pandemic.

EM-DAT is the most widely employed resource for studying 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–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 data of 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).

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 start date and end date of each disaster. Geographical variables include 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 includes data on economic damages 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 parents' ages, schooling levels, whether parents are alive, and whether parents are co-resident 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 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 ages 5 to 17 and math-learning skills for children ages 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). They 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 children do not move and reside 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 migratory history utilizing two pieces of information: years living in current location and 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 maternal duration of residency in the current location. There are two key reasons why 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 (Statistics (BBS) and 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 percent of the years since the birth of their child selected for the 5 to 17 Child Questionnaire.

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7. We provide more details on measures construction 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 Kyrgyzstan, 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. But we only observe first-level administrative divisions (division) for prior locations of mothers. For Kyrgyzstan, 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 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.

Furthermore, across countries and on average, between 83 and 96 percent 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 at 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 of 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 birth year-month, interview year-month, disaster start year-month and end year-month, and child and disaster location 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_{ilg}^p, which equals one if type p intensity disaster took place in location l when child i—who resides in l—is 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 child-specific first and last age-in-month for each time segment j.[10] To analyze child disaster exposure within each time segment j, we aggregate over DI_{ilg}^p to generate

$$DM_{ilj}^p = \sum_{g=FM_{ij}}^{LM_{ij}} DI_{ilg}^p$$
$$\text{and } DB_{ilj}^p = 1\{DM_{ilj}^p \geq 1\}\,.$$

(1)

DM_{ilj}^p captures the number of months child i in location l experiences disaster of type p during time segment j, and DB_{ilj}^p indicates if the child experiences 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 exposures variables. The periods include the most recent year prior to the survey month (including 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 information are available for all children in our MICS

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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-month windows depending on child age when surveyed. Hence we include an individual-specific i subscript for FM_{ij} and LM_{ij}.

sample.[11] The oldest child in the sample was born in 1999 Dec. 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, B to include only floods, and 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 B and C to consider only severe floods. In the main results, we consider the effects of exposures to type A, B, C, and D disaster types, and present them in successive columns of our regression tables. Having various types of disaster intensities provides the possibility for robustness checks on disaster experience construction. Out of a total of 355 disaster events, 155 were categorized as floods, included in type B disaster classification. Severe disasters accounted for 174 out of the 355 events, forming the basis for type C disaster intensity. Within this subset, floods emerged as the most frequent, with 93 incidents, which were subsequently classified under type D disaster intensities.

3 Summary Statistics

3.1 Summary Statistics for Children and Parents

3.1.1 Sample

As stated prior, 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 with which district (administrative level two) they live in while children from Kyrgyzstan are identified with 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 distribution of sample by country and age in Figure 1. The average enrollment rate in the current school year when children are surveyed is 79% and 90% of the children ad 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 father ever-educated are slightly higher than for mothers. But it is also noticeable

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11. Interview calendar day is observed for sample children as well, but we only use year and month information to match disasters to child life-cycle because birth calendar day is not observed for all children.

that father information is collected for a smaller sub-sample than that for mothers. 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 percent of the children in the sample no longer have fathers who are alive and 25 percent of the sample are no longer living with their fathers. In contrast, the shares of children with mothers who are alive are above 96 percent across all ages, and the shares of children living with mothers are larger than 85 percent across all ages.

In Appendix Table C.2 and Figure C.3, we break down the sample by countries and show information on mothers' educational levels and whether children live with parents. In Turkmenistan, Kyrgyzstan, Thailand, and Mongolia, the shares of mothers who have been ever-enrolled are larger than 94 percent; In contrast, in Bangladesh and the three provinces of Pakistan, the shares are 74 and 36 percent, respectively.[12] In Kyrgyzstan, the shares of mothers with higher than secondary education and ever-enrolled are both higher than 90 percent, but in all other countries, the shares of mothers with secondary education account for between 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, 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 countries. 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 enrollment status in the survey year. Compared to boys, current enrollment for girls are 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 ages 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 percent of the samples by age 8 in all countries except for Pakistan, where over 30 percent of children aged 17 years 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.

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12. According to a report on Pakistan from DHS (National Institute of Population Studies and ICF 2019), half of ever-married women aged 15 to 49 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 completed grade by a child at the time of the survey. Results on attainment by age and country are shown in Figure 6. Average attainment for children (5-17 years old) varies by countries, with Mongolian children having the highest and children from Pakistan having the lowest average attainment. Compared to boys, average attainment for girls is higher in Bangladesh, Nepal and Thailand, significantly lower in Pakistan, and similar in other countries.

Test Score. 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 the lowest in Pakistan. Test scores are similar by gender, 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, Kyrgyzstan, and Thailand have relatively high average scores that rise gradually across age groups. Children from Nepal and Bangladesh have medium levels of average performances that increase steeply as children age. Children from Pakistan have the lowest math-test scores, and average scores have slow growth as age increases. In particular, the average math-test score in the Sindh province of Pakistan at age 14 is less than half of the average test score for children in Thailand at age 7.

3.2 EM-DAT Disaster Experience

With the linked MICS and EM-DAT disaster-exposure data, we consider the share of children from the MICS sample experiencing 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 months and countries. 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 as 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 going to school and 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 probabilities 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 attainments (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 with 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 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 attainments 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 enrollment status of child i living in location l in last school year $t-1$. A_{ilt} is grade completed at 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 parents, and whether 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 less disasters. Through location fixed effects, we control for these to the extent 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 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 to Disaster Shocks. We model educational achievement—MICS-administered math-test scores—as the output of 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 assessting the het-

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13. We consider the survey interview timing by controlling for survey year × 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 at 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 most-recent year), the years between the second most-recent year and first 1,000 days (a span that we describe as mid-child life), and the first 1,000 days. We compare test scores, controlling for location fixed effects, μ_l, survey-timing fixed effects, μ_m, child-age fixed effects, $\mu_{g_i(m)}$, and country- and attainment-specific fixed effects, $\mu_{c(l),A_i(m)}$.

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

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

where $\beta_{g_i(m),j}^p$ is exposure to type p disaster intensity in period j, which is specific to child aged $g_i(m)$ at survey month m. Our estimation strategy exploits heterogeneities in disaster histories within locations and across individuals. In practice, because conditional on location and age-in-month jointly, there are no variations in child exposure histories, we cannot estimate Eq. (4) with separate $\beta_{g_i(m),j}^p$ for each age-in-month. 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 analysis based on the enrollment model, we find that after lower primary grades, there are weak negative effects of recent disaster exposures on enrollments, and persistent negative direct effects of early life disaster exposures

14

on enrollments. We find generally larger negative impacts on enrollments for boys, and greater enrollment impacts from exposures 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-disasters 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 intensity disasters.

5.1   Enrollments and Disaster Experiences

We estimate Eq. (2) using a linear probability model and present results in Table 5. We consider both the effects of having experienced any disaster in the most recent 12 months as well as the number of months experiencing 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 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 child being female, parental survival and parent-child co-residency status, and if mother is ever-schooled 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 categories or severity. Averaging across children between 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 disasters exposure would, on average, lead to about a one percentage point reduction in enrollments.

In columns (2) to (4), we move beyond average effects across all disasters and compare children with and without floods, severe disasters, and severe floods exposures (see Section 2.2). In column (2) of Table 5, compared to children who did not experience floods, we find that children with recent floods exposures have 1.2 percentage points lower rate of current enrollments. However, the recent-exposure effects are insignificant for severe disasters and severe-floods exposures. For early life disaster exposures, we find that the estimated effects of floods (column 2) and severe disasters (column 3) exposures double the negative "all disasters" estimates from column (1), and the effects of severe-floods (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 disasters 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 both lagged enrollments and attainments (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 girls have 0.6 percentage points lower enrollments than boys, having a mother ever 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 increased 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 0.5 percentage points reduction in enrollments.

5.2 Heterogeneous Effects on Enrollments Across Ages and Genders

In this section, we continue to estimate Eq. (2) using linear probability models, but 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 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 recent disasters exposure on enrollments for children during 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 recent floods and severe-floods exposures for boys 9 to 17, with recent-severe-floods 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 points reduction in enrollments. However, recent-severe-flood exposures lead to 3.6 percentage points 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 risks for staying at damaged homes.

Similar to the recent-disasters results, we also find consistent negative direct effects of early disasters experiences on enrollments for children 9 to 17, with upper-primary boys experiencing the strongest effects—an additional month of early disasters 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 points reductions for boys' current enrollments, and 0.3 percentage points reduction for girls' enrollments. Interestingly,

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14. In Bangladesh, Mongolia, Nepal, and Pakistan, the official primary-school entrance age is 6 and the primary-school cycle spans 5 years. In Kyrgyzstan, 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.

we find negative direct effects of early disasters exposures on enrollments for girls 5 to 8, but no effects for boys, which indicates an early disaster exposures 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 have 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 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 recent disasters experience on enrollments in all three age groups, as well as negative impacts of direct early life disasters exposure on enrollments, but more significantly for children 5 to 8. For Bangladesh, we find that both recent and early disasters 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 types, and includes various fixed effects and individual-specific controls. Coefficient estimates are in 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 disasters 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 percentiles of early life disasters exposures would lead to average test score reductions of 0.09 and 0.04 standard deviations in Kyrgyzstan and Nepal, which have the second lowest and second highest math-test score standard deviations in our sample.

17

The estimated average effects of disasters exposures on math skills by disaster types 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 is twice as severe as the negative effects of early life exposures to "all disasters". We also find imprecisely estimated negative effects of severe floods exposures, but find close to zero effects for severe disasters 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 each type and severity of disasters experience—they are based on comparing between children with a particular type and severity of disasters exposures 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 columns of Table 8. Girls are found to have lower scores than boys holding other factors constant. Having a mother ever 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 co-reside with the child.

5.4 Heterogeneous Effects on Math Skills Across Ages and Genders

In this section, we estimate heterogeneous effects of life-cycle disaster exposures on math scores by age groups in Table 9 and by joint age and gender groups in Table 10. As before, we present results across disaster types in four columns. Although the effects of disasters 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 disasters 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 floods effects magnitudes approximately doubling the "all disasters" effects.

In Tables 9 and 10, we find early life disasters' negative effects on math-test scores for lower-primary and post-primary children are similar in magnitudes as 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 magnitudes as the "all disasters" effects. Breaking down results by gender in Table 10, across disaster types, we continue to find consistently negative but generally imprecisely estimated early-life disasters exposures 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 disasters exposures leads to 0.041 and 0.036 points reductions in early-primary and 0.041 and 0.018 points reductions in post-primary math-test scores; the post-primary estimates for girls and boys, respectively, are about 30 percent larger and 40 percent 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 greater catch-up with age, which helps to mitigate the initial negative effects.

Generally, compared to later disasters exposures, we find that early disasters 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 the most affected (Andrabi, Daniels, and Das 2021). The low height-for-age 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 countries and age groups. Similar to the overall findings, we find consistent negative mid-child life disasters exposure effect 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. 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 emphasis on exposures in the 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 literature addressing the immediate and lasting effects of disaster shocks in early life on children's human-capital outcomes, though 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 a global record of natural disasters, we are able to exploit cross-location and cross-time variations in disasters exposures across children and our results provide a broader perspective than studies limited to single countries. Third, rather than limit 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 on 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' performance. Additionally, we show that the exposures particularly to floods, 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							
Kyrgyzstan	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 differs 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 age	37.78	8.68	2.00	95.00	132143
Father 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 until 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 second panel, and location-specific or child-and-location-specific disaster experience indicators in the third panel. DB^A is an indicator equal one if there is any type of disaster in the designated time span, zero if not. For example, DB^A in Survey Month being one 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
Kyrgyzstan					
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 countries. Our sample is dominated by children from Bangladesh and Pakistan. This table includes enrollment status for current and last school year. 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
Kyrgyzstan					
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 countries. The column "Mean" shows the share of children who have experienced any type of disaster shocks in each period. DB^A is indicator equal one if there is any type of disaster in the designated time span, zero if not. For example, DB^A in Survey Month equals one means there has been disaster happening 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 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 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 Equation 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 disaster in first 1,000 days is about 3 months. About 57% of children in whole sample have experienced natural disaster in most recent 12 months. For the disaster intensity type, we consider type A as all disasters, B as only flood, C as severe disasters which is defined as causing more than 500 casualties or 5,000 people affected. Type D combines B and C considering only severe flood. Having various types of disaster intensity provides us 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 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 of disaster effects on enrollment corresponding to Equation 2 by interacting disaster shocks with age groups. For children in age 5-8, about 55% of them have experienced natural disaster in most recent 12 months, while 56% and 59% of children in age 9-12 and in age 13-17 have disaster shock in this time span, respectively. The average number of months with disaster in first 1,000 days for children in age 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 flood, C as severe disasters which is defined as causing more than 500 casualties or 5,000 people affected. Type D combines B and C considering only severe flood. Having various types of disaster intensity provides us 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 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 of disaster effects on enrollments. This corresponds to Equation 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 natural disaster in most recent 12 months. The average number of months with disaster in first 1,000 days for children in age 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 flood, C as severe disasters which is defined as causing more than 500 casualties or 5,000 people affected. Type D combines B and C considering only severe flood. Having various types of disaster intensity provides us 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 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 Equation 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 survey month. The length of mid-child life varies among individuals with an average of all children being 84 months (S.D. is 46). About 57% of children in whole sample have experienced natural disaster in most recent 12 months. The average number of months with disaster in first 1,000 days is about 3 months. The average number of months with 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 standard deviation 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 flood, C as severe disasters which is defined as causing more than 500 casualties or 5,000 people affected. Type D combines B and C considering only severe flood. Having various types of disaster intensity provides us 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 of disaster effects on math-test scores. This corresponds to Equation 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 survey month. The average number of months covered in mid-life child is 53 months, 90 months, and 120 months for children in age 7-9, age 10-12, and age 13-14, respectively. For children in each age group, about 56% of them have experienced natural disaster in most recent 12 months. The average number of months with disaster in first 1,000 days for children in age 7-9, 10-12, and 13-14 is about 2 months, 3 months, and 4 months, respectively. The average number of months with disaster in mid-child life is about 5.4 months, 8 months, and 10.5 months for children in age 7-9, 10-12, and 13-14, respectively. The average math test score for children in age 7 to 9 is 12.3 with standard deviation 7.6. The average math test score for children in age 9 to 12 is 15.2 and standard deviation is 7. For the oldest children group in age 13 to 14, average math test score average math test score is 15.9 with standard deviation 6.9. The distribution of math test score across ages and countries is shown in Figure 7. For the disaster intensity type, we consider type A as all disasters, B as only flood, C as severe disasters which is defined as causing more than 500 casualties or 5,000 people affected. Type D combines B and C considering only severe flood. Having various types of disaster intensity provides us 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 of disaster effects on math-test scores. This corresponds to Equation 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 survey month. The average number of months covered in mid-life child is 53 months, 90 months, and 120 months for children in age 7-9, age 10-12, and age 13-14, respectively. For both boys and girls in each age group, about 56% have experienced natural disaster in most recent 12 months. The average number of months with disaster in first 1,000 days for children of both genders in age 7-9, 10-12, and 13-14 is about 2 months, 3 months, and 4 months, respectively. The average number of months with disaster in mid-child life is about 5.4 months, 8 months, and 10.5 months for children in age 7-9, 10-12, and 13-14, respectively, which do not vary across genders. The average math test score for boys in age 7 to 9 is 12.4 (standard deviation is 7.6), which is slightly higher than girls (12.1). The average math test score for boys in age 9 to 12 is 15.4 and standard deviation is 7. Girls are observed with on average 15 for math score. For the oldest children group in age 13 to 14, average math test scores are 16 (standard deviation is 6.6) for boys and 15.6 for girls (standard deviation is 7). The distribution of math test score across ages and countries is shown in Figure 7. For the disaster intensity type, we consider type A as all disasters, B as only flood, C as severe disasters which is defined as causing more than 500 casualties or 5,000 people affected. Type D combines B and C considering only severe flood. Having various types of disaster intensity provides us 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
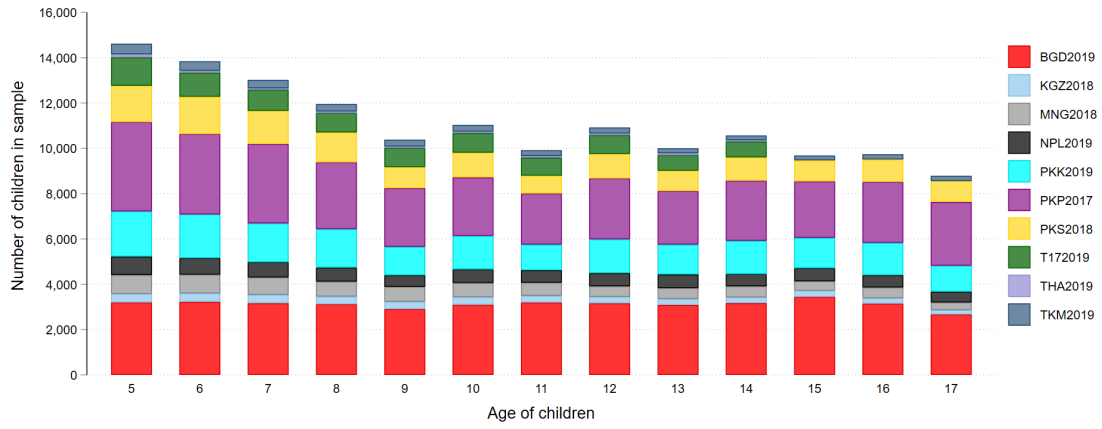

(b) Sample Size Across Gender and Ages
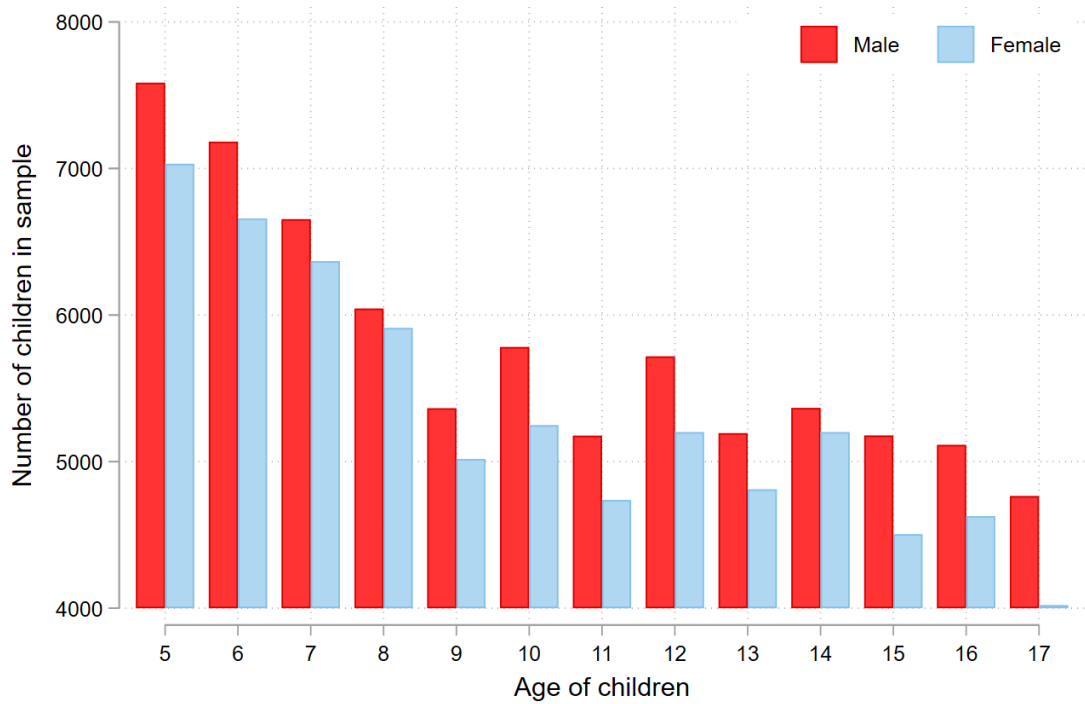
Note: Panel (a) shows number of children in each age and country. There are 144,471 children in full sample dominated by Bangladesh and Pakistan. For every age and country, there are more boys interviewed than girls. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (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)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure 2: Parental Presence by Children's Ages

(a) Share of Children with Mother or Father Alive by Ages
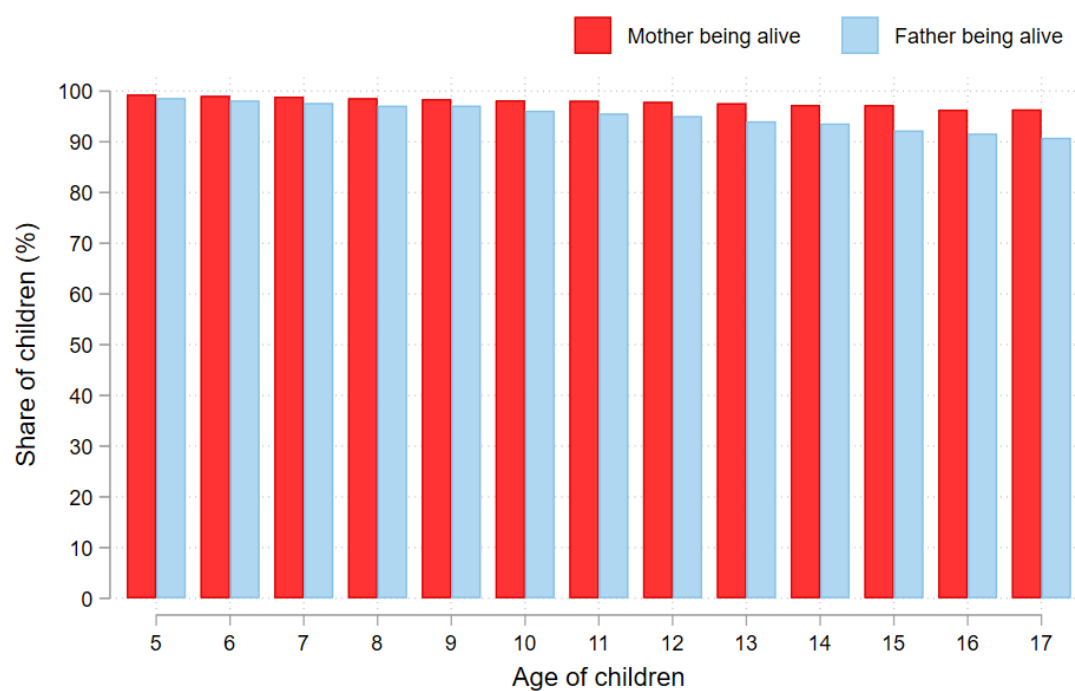
(b) Share of Children Living with Mother or Father by Ages
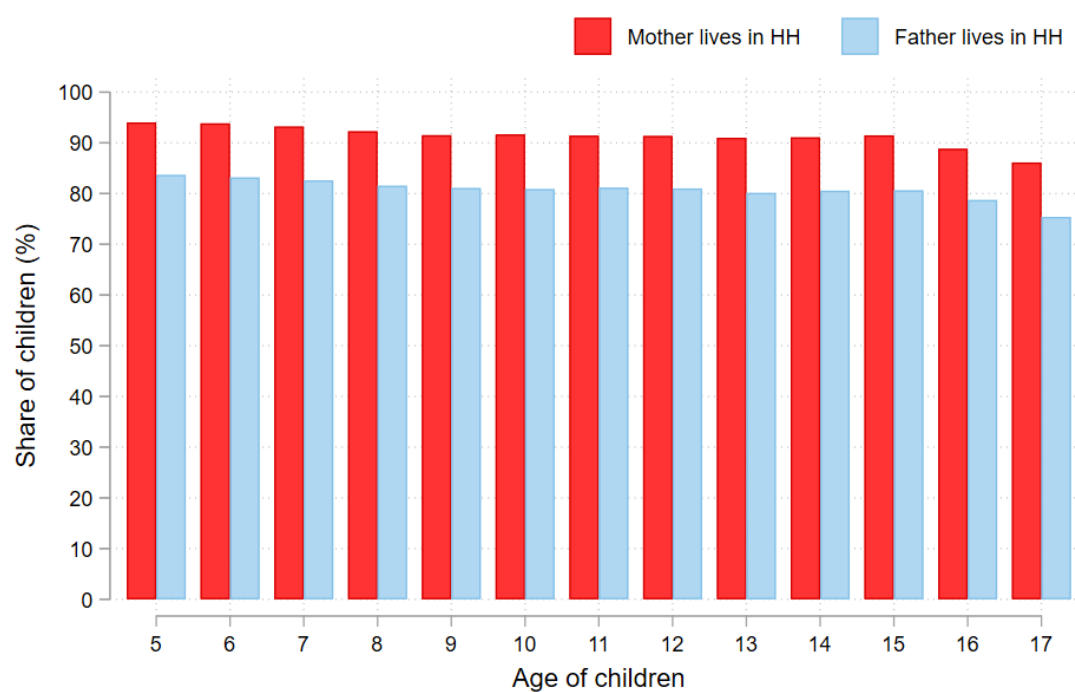
Note: Panel (a) shows the share of children with mother or father who is alive by child ages. Panel (b) shows the share of children living with either mother or father by ages.

Figure 3: Enrollment Fraction in Survey Year

(a) Enrollment Fraction in Survey Year by Ages and Countries
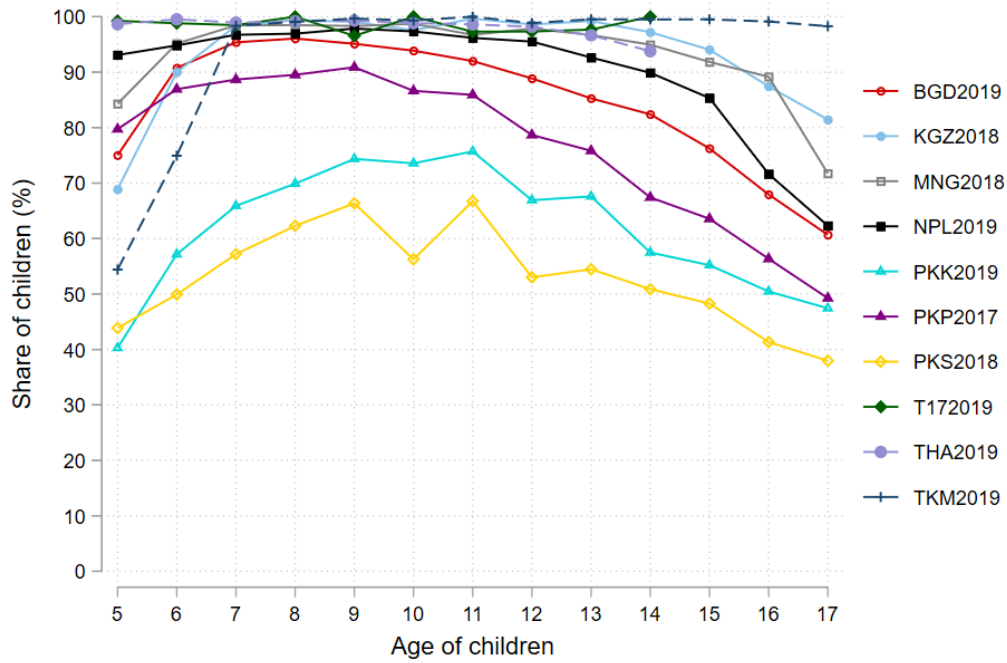
(b) Enrollment Fraction in Survey by Gender and Country
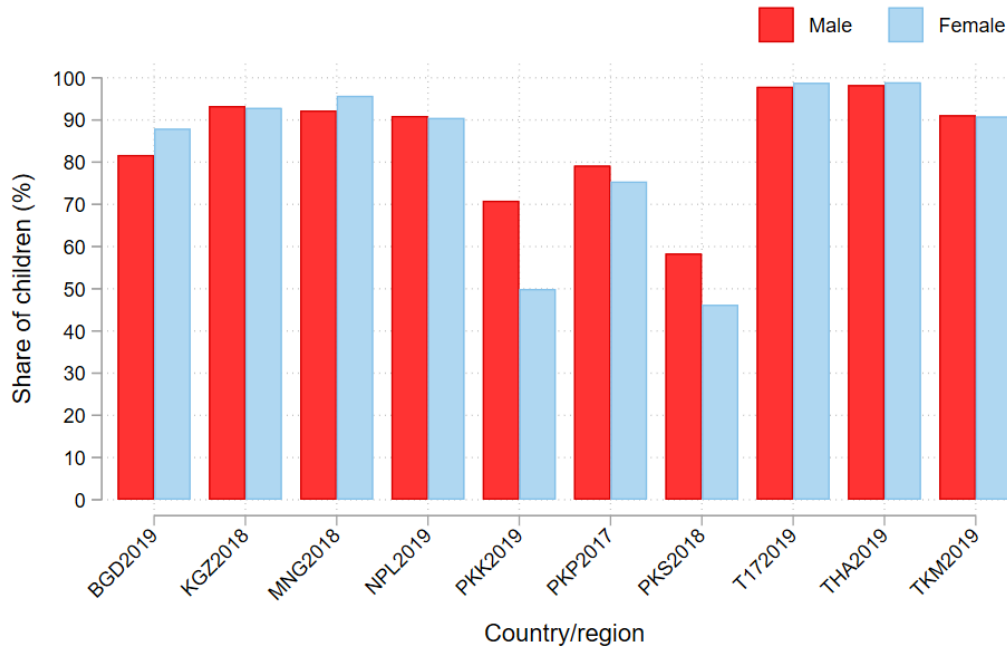
Note: Enrollment fraction in survey year. In Thailand, data are observed only up to age 14, in all other countries, data are available up to age 17. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure 4: Share of Children Ever-enrolled

(a) Share of Children Ever Enrolled in School by Ages and Countries
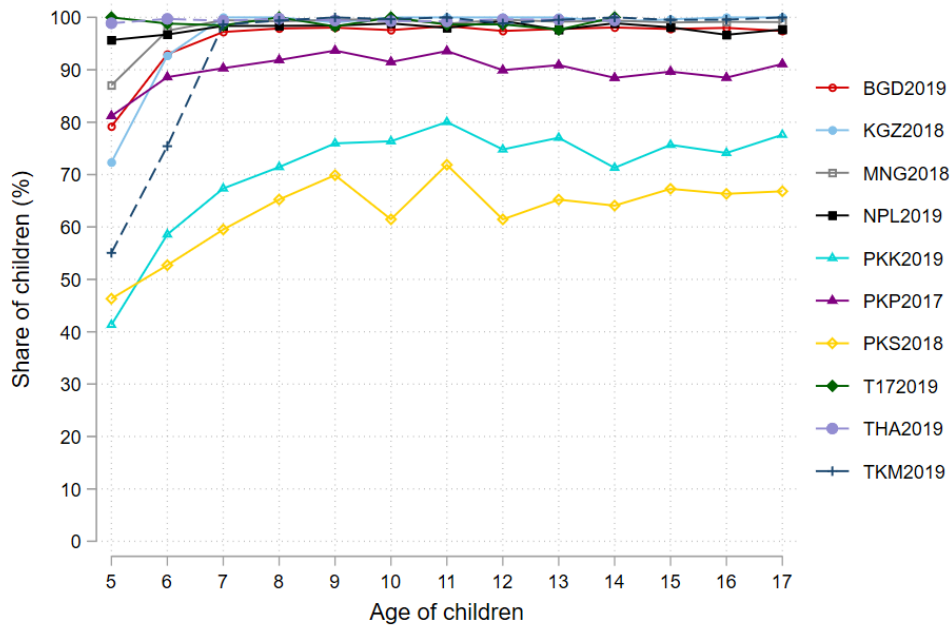
(b) Share of Children Ever Enrolled in School by Gender and Countries
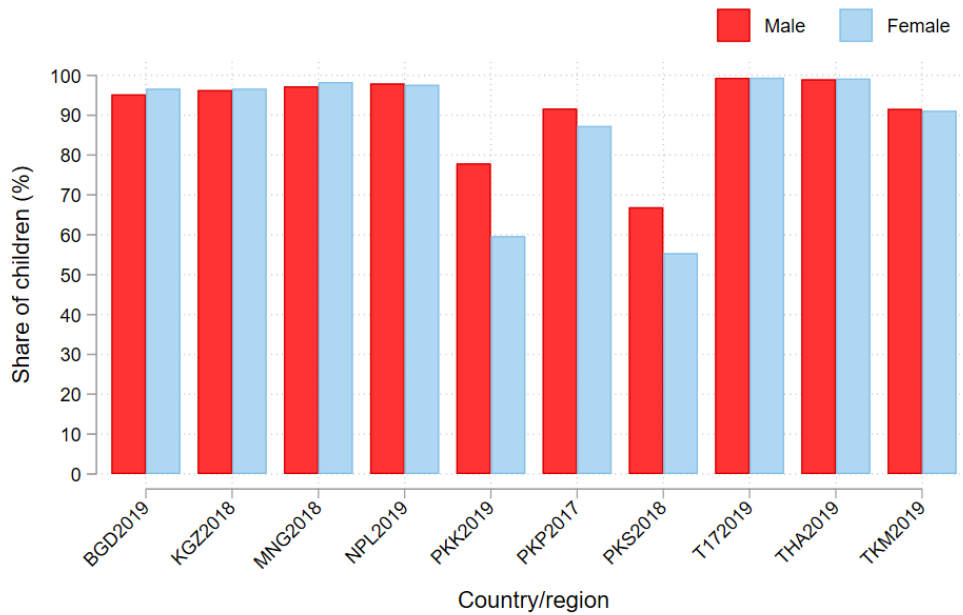
Note: The survey asks if a child has ever been enrolled in school. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure 5: Enrollment Transition Probabilities By Ages

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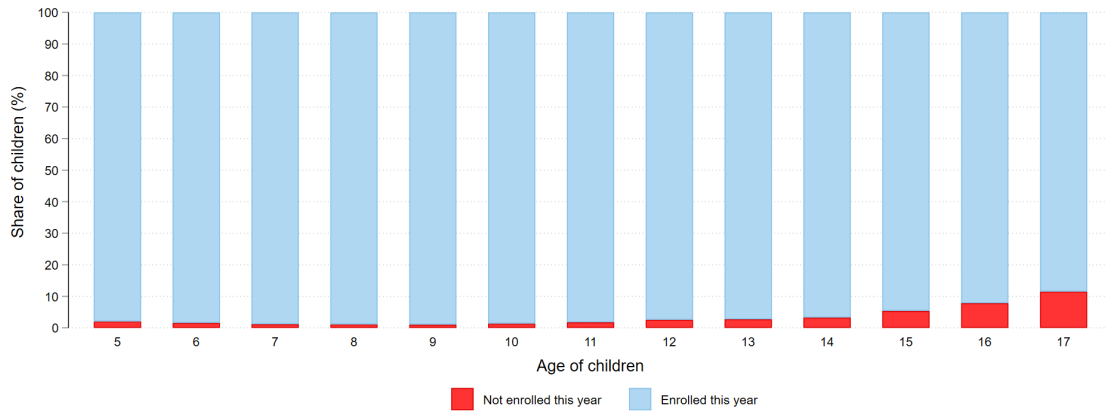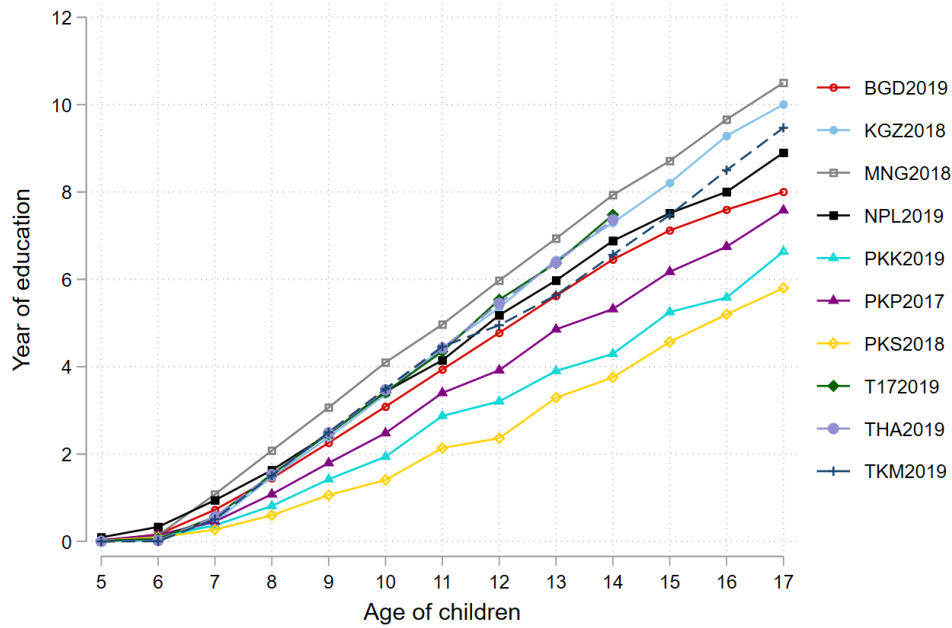

(b) Enrollment Fraction in Survey Year Conditional on **Not Being Enrolled** in the Previous Year
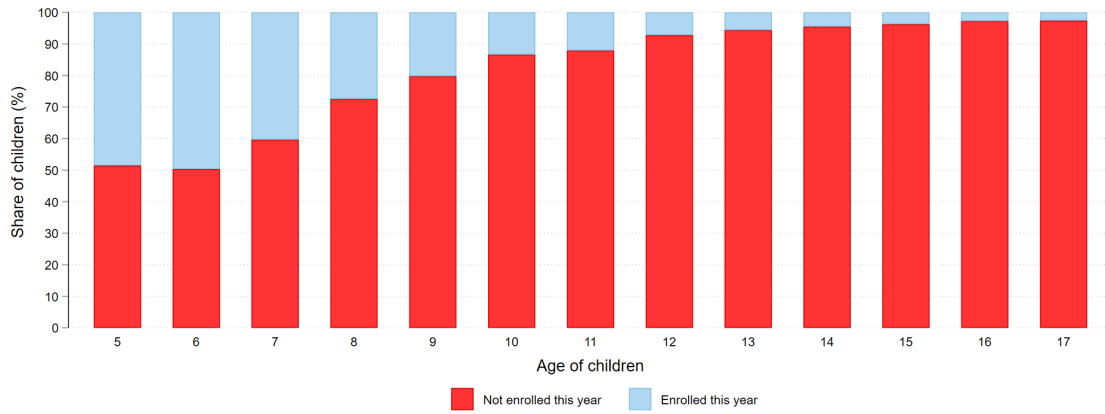
Note: Enrollment fraction in survey year conditional on being **Enrolled** previous year. The results show conditional probabilities.

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

(a) Average Grades of Schooling Completed by Ages and Countries

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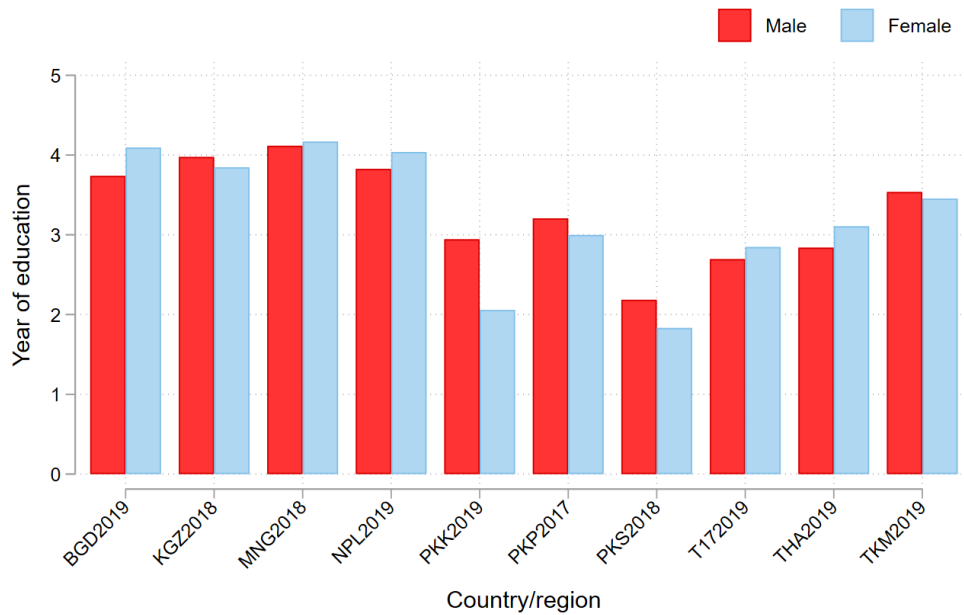
Note: In Thailand, data are observed only up to age 14, in all other countries, data are available up to age 17. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**),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

Figure 7: Distribution of Math Scores

(a) Average of Math Scores by Ages and Countries
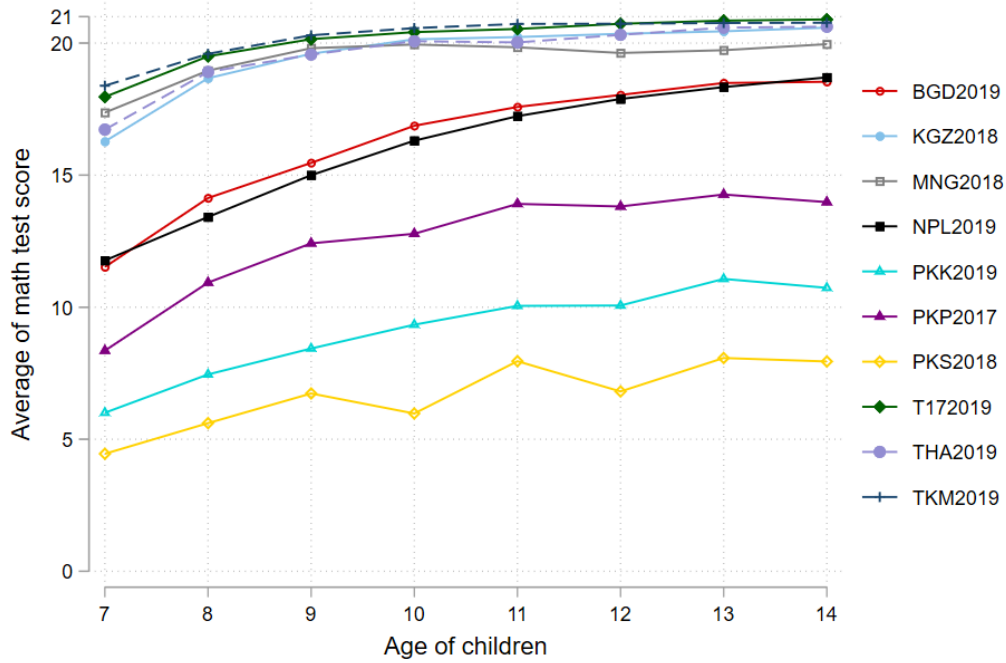
(b) Average of Math Scores by Gender and Countries (Age 7-14)
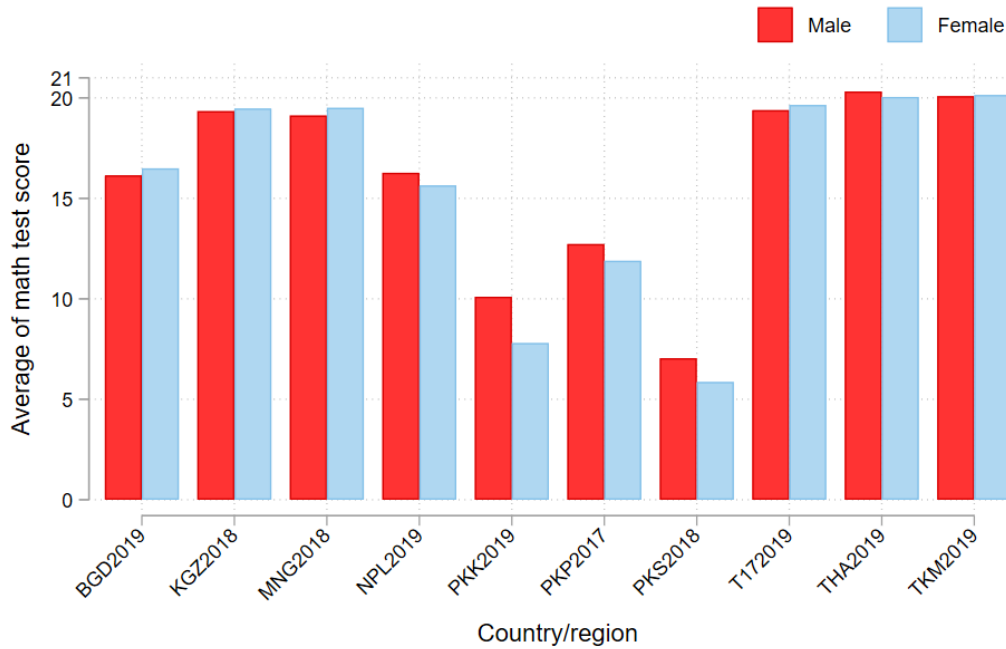
Note: Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure 8: Share of Location-month with Disasters in Each Calendar Month over 20 Years

(a) All Countries

(b) Bangladesh Only

(c) Pakistan Only

(d) Other Countries
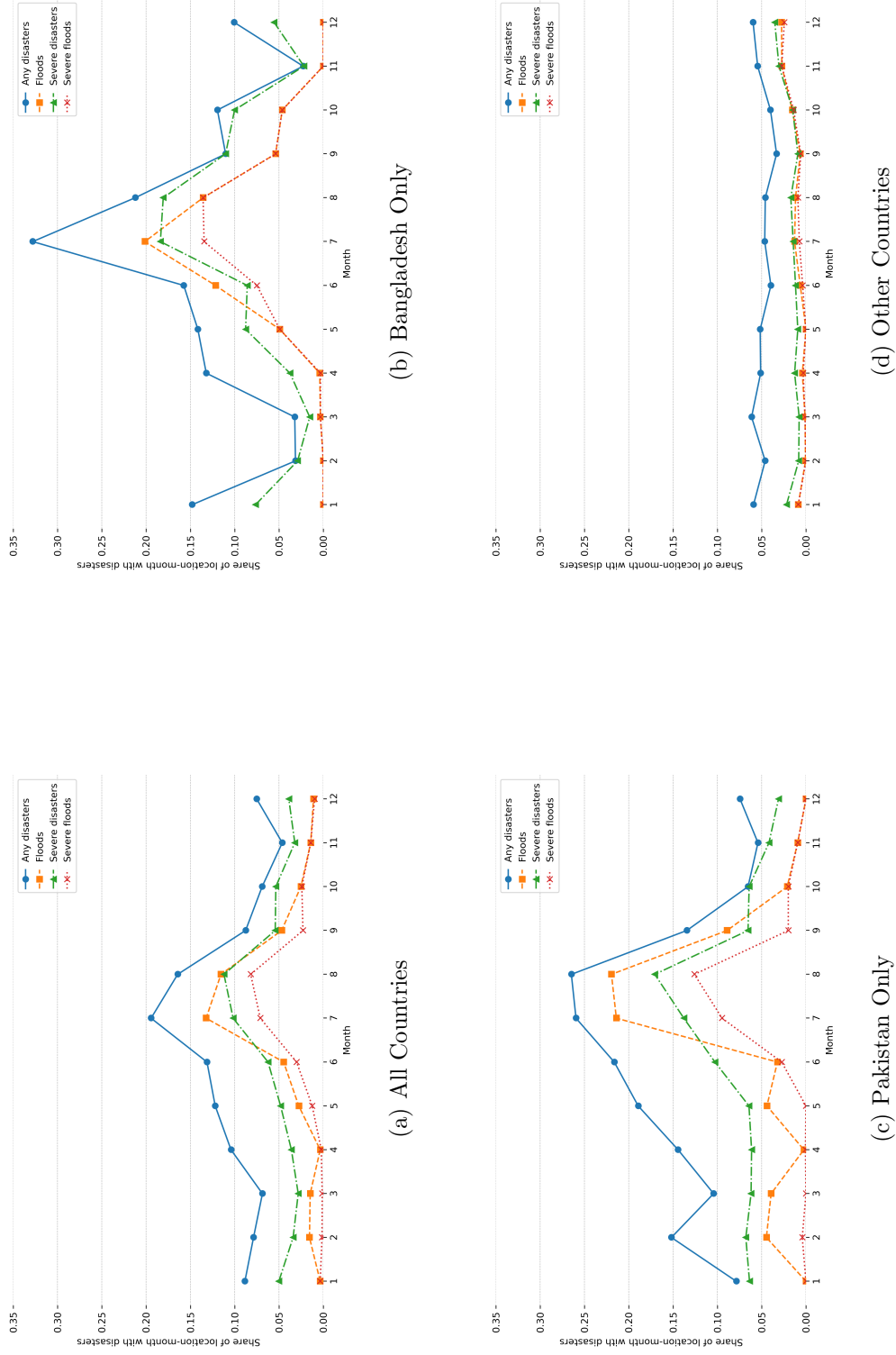
Note. For each location in every month from latest survey month to 20 years prior to the survey, we construct a disaster indicator using EM-DAT Data. For all locations in previous 20 years, share of location-month with disaster shock of each type is shown cross calendar months of the year.

References

Adhvaryu, Achyuta, Teresa Molina, Anant Nyshadham, and Jorge Tamayo. 2024. "Helping Children Catch Up: Early Life Shocks and the PROGRESA Experiment." *The Economic Journal* 134, no. 657 (January 1, 2024): 1–22. https://doi.org/10.1093/ej/uead067.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Chang, Grace, Marta Favara, and Rafael Novella. 2022. "The Origins of Cognitive Skills and Non-Cognitive Skills: The Long-Term Effect of in-Utero Rainfall Shocks in India." *Eco-

nomics & Human Biology 44 (January): 101089. https://doi.org/10.1016/j.ehb.2021.101089.

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

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

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

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

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

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

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

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

De Vreyer, Philippe, Nathalie Guilbert, and Sandrine Mesple-Somps. 2015. "Impact of Natural Disasters on Education Outcomes: Evidence from the 1987–89 Locust Plague in Mali†." Journal of African Economies 24, no. 1 (January 1, 2015): 57–100. https://doi.org/10.1093/jae/eju018.

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

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

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

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

UN-ESCAP, United Nations Economic and Social Commission for Asia and the Pacific. 2023. "Seizing the Moment : Targeting Transformative Disaster Risk Resilience." Asia Pacific

Disaster Report (APDR) Area(s) of Work Building Resilience to Disasters (SDG 13. Climate Action 2023). https://doi.org/10.18356/25206796-2020-13.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Intergovernmental Panel on Climate Change. 2022. *Global Warming of 1.5°c: IPCC Special Report on Impacts of Global Warming of 1.5°c Above Pre-Industrial Levels in Context of Strengthening Response to Climate Change, Sustainable Development, and Efforts to Eradicate Poverty.* Cambridge: Cambridge University Press. https://doi.org/10.1017/9781009157940.

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

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

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

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

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

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

Liu, Elaine M, Jin-Tan Liu, and Tzu-Yin Hazel Tseng. 2022a. "Fetal Origins of Mental Health: Evidence from Natural Disasters in Taiwan." *Working Paper.*

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

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

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

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

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

———. 2021b. "Global Estimates of the Implications of COVID-19-Related Preprimary School Closures for Children's Instructional Access, Development, Learning, and Economic Wellbeing." *Child Development* 92, no. 5 (September): e883–e899. https://doi.org/10.1111/cdev.13658.

National Institute of Population Studies, (NIPS) [Pakistan], and ICF. 2019. "2017-18 Pakistan Demographic and Health Survey Key Findings." *Islamabad, Pakistan, and Rockville, Maryland, USA: NIPS and ICF.*

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

———. 2006. "Assessing the Impact of a School Subsidy Program in Mexico: Using a Social Experiment to Validate a Dynamic Behavioral Model of Child Schooling and Fertility."

American Economic Review 96, no. 5 (December): 1384–1417. https://doi.org/10.1257/aer.96.5.1384.

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

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

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

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

United Nations. 2021. *Climate and Weather Related Disasters Surge Five-Fold Over 50 Years, but Early Warnings Save Lives.* UN News: Global perspective, human stories, September.

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

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

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

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) that 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 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 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; (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 disciplines are 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: 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 are 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 (Kyrgyzstan (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 for children on 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, grade attended last school year, and 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 prefixed to 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 includes 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 "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 (CB5/ED5) attended, grade attended in last year (CB10/ED16), and grade attended in 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 missing value for *edu_everschool*, by 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 whom this skip-pattern logic was not followed. Aggregating over the 18,020 children with "No" as 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 enrollment 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 missing value with zero if $E_{ever} = 0$. We set the current enrollment status variable E_t equal to *edu_enrolthisy* and replace 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 are:

- $E_{ever} = 0$ 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 size 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 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 whole sample. Among them, 104,196 children along path A, 3,099 children along path B, 9,178 children along path C, 8,852 children along path D, and 17,956 children along 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 path 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, it should be that *edu_yoe_lasty* is 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 start of last year A_{t-1}, and attainment at 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 grade in 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 enrolled-grade last year (*edu_yoe_lasty*) in stead of enrolled-grade this year; path C is treated identically as 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; for path E, the highest attainment is zero.

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

We use the following logic to construct A_t: Attainment at start of this school year A_t is the enrolled-grade last year minus 1 for path A; children on path B are enrolled last year but not enrolled this year, so $A_t = A_{max}$; for path C, since the child is not enrolled in last year but enrolled in this year, we know the attainment at start of this year should be the enrolled-grade in this year minus one; 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 is 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* = $(69 - \text{FL20B})$; 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 word correctly, and if the child did not try to read 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 variable *read_score_comp* by counting the number of questions the child answered correctly. At last, we generate the total reading score, *read_score_total*, by aggregating over *read_score_wordcorrect* and *read_score_comp*. Appendix Figure C.7 presents distribution of *read_score_total*.

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

Component (1): 6 symbol recognition questions (e.g., for the numbers 9, 12, etc.)
Component (2): 5 number comparison questions (e.g., between 7 and 5 or 65 and 67)
Component (3): 5 addition questions
Component (4): 5 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 country 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, 0 if answered incorrectly or not attempted. We construct the variable *math_score_total* as the sum of component-specific scores *math_score_sym*, *math_score_big*, *math_score_add*, and math_score_next. Figure 7 presents distribution of *math_score_total*.

As exceptions, the surveys in Kyrgyzstan 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 Kyrgyzstan, 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; 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 Household Questionnaire. Otherwise, they are 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 "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 child age from HL6 and CB3 questions. We obtain 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 mother's and father's birth years and months from question HL5, and use question HL6 to confirm their ages.

In both "fs" and "hl" files, "melevel" and "felevel" variables report maternal and paternal educational attainment. We use "melevel" from "fs" file if data is available and otherwise use the information from the "hl" file. We use "felevel" from the "hl" file for father's education. Appendix Figure C.3 presents the distributions of share of mother ever 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 these information, we construct indicators of maternal, paternal, and joint parental loss status and parent-child co-residency status. Figure 2 present share of children parental loss and co-residing parents. Appendix Figure C.4 presents maternal and paternal joint loss status by country and age. Appendix Figure C.5 presents 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 to download disaster files for certain types of events and specific area. 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 the 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 are recorded separately for each country.

B.2   Context and Impact Variables

Information associated with each disaster can be categorized into context and impact variables. 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

Geographical information includes variables for the country, region, continent, and river basin where the disaster took place, and also includes coordinates for the epicenter of earthquakes. Crucially, EM-DAT reports the administrative-level and name of locations affected by each disaster. This project relies on these information to link between disaster locations and locations where MICS6 children reside.

Temporal information includes variables for start and end dates of each disaster. We use these temporal information to match the timing of disasters to the life-cycle of each child. Specifically, given location information and combining birth dates, survey dates, and disaster starts and duration, we generate a child-level monthly panel dataset that records for each child at each age-in-month 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 measured by total estimated damages, reconstruction cost and insured losses associated with that event.

We jointly use the number of death 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 disaster 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 this flood started on August 5, 2016 and ended on August 8, 2016. The four-day disaster led to 32 death 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 names 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 that MICS6 children reside at. When "GeoLocations" is unavailable, we match after searching through the "Location" variable names across location names across administrative levels.

55

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 children. Figures C.1 and C.2 present shares of the sample reporting math and reading test scores, respectively. Figures C.3, C.4 and C.5 plot parental and household characteristics. Distribution 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 less controls for effects of "all disasters" (Type A) on enrollments. Table C.5 shows results for effects of disaster exposures on enrollments with various disaster exposure measures. Tables C.6 presents heterogeneity analysis for the effects of disasters exposures on enrollments by age and country groups. For 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 age	35.88	8.24	2.00	80.00	37,494
Father age	43.66	9.75	7.00	95.00	33,485
Kyrgyzstan					
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 age	38.52	8.24	21.00	76.00	3,303
Father 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 age	37.66	7.28	20.00	77.00	6,612
Father 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 age	35.91	8.64	13.00	95.00	7,083
Father 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 age	39.09	9.00	18.00	95.00	67,435
Father 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 age	37.02	7.40	18.00	61.00	6,632
Father 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 age	37.51	7.33	22.00	95.00	3,584
Father age	38.96	7.39	23.00	77.00	3,232

Note: This table shows summary statistics for some demographic characteristics by countries. For example, in Bangladesh, the average age of children is about 11 years, 48% of 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
Kyrgyzstan					
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 countries.

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

| | Percentiles | | | | Mean | SD | Obs |
	5th	10th	15th	20th			
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
Kyrgyzstan							
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 one child is 10 years old, and the mother has been living in the current location for 7 years, then this number calculated as 0.7.

Table C.4: Effects of disasters on enrollments

	(1)	(2)	(3)
Had disaster in 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 Equation 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 disaster in first 1,000 days is about 3 months. About 57% of children in whole sample have experienced natural disaster in 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.	recent 3 mo.	recent 12 mo.	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 Equation 2 using different measures for recent shocks. We consider binary indicator of any type of disaster that happened in survey month (column 1), in most recent 3 months (column 2), and in most recent year (column 3). Then we use the number of month when there was any type of natural disaster in 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 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 heterogeneous analysis across countries and ages of disaster effects on enrollments. This is corresponded with Equation 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 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 in age 5-8, age 9-12, and age 13-17 have on average 1, 2, and 4 months in disaster, respectively. The share is higher for Bangladesh as children in age 5-8, 9-12, and 13-17 are in disaster for 2, 4, 5 months during first 1,000 days, respectively. In other countries, children in age 5-8 and age 9-12 have on average 3.5 months in disaster, while children in age 13-17 have experienced 1.7 months of disaster. 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 Equation 3 using different measures for disaster shocks. In each column, four shocks covering one child's disaster exposure history is included representing four time spans: first 1,000 days, mid-child life (time between first 1,000 days and most recent 2 years), 1 year prior 12 months ago compared to 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 heterogeneous analysis across countries and ages of disaster effects on math scores. This is corresponded with Equation 3 with interaction 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 Ages and Countries
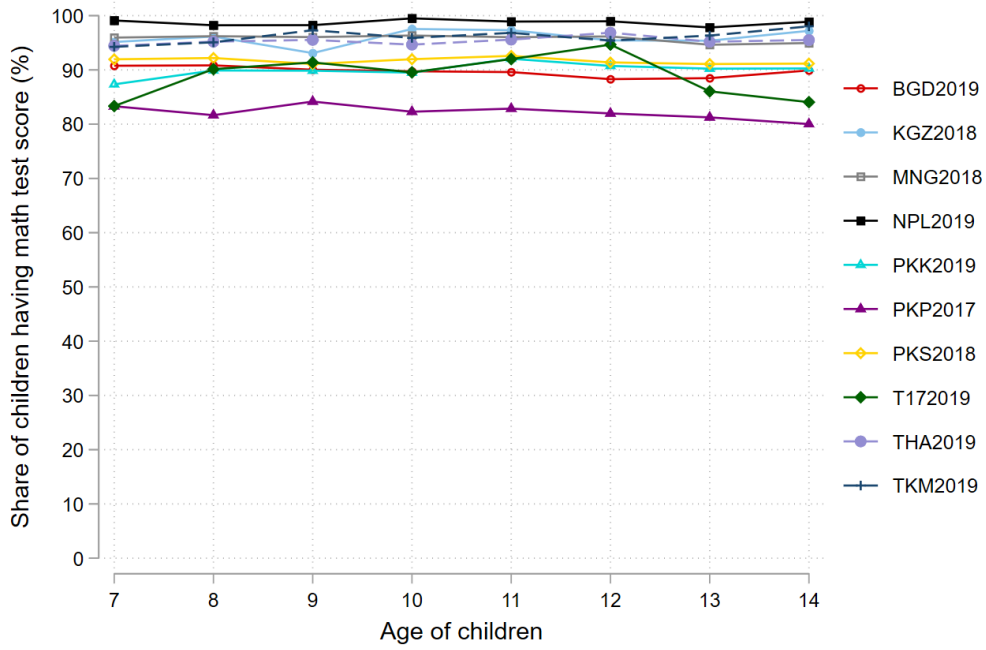
(b) Math Test Sample Size by Enrollment Status in Current Year Across Countries
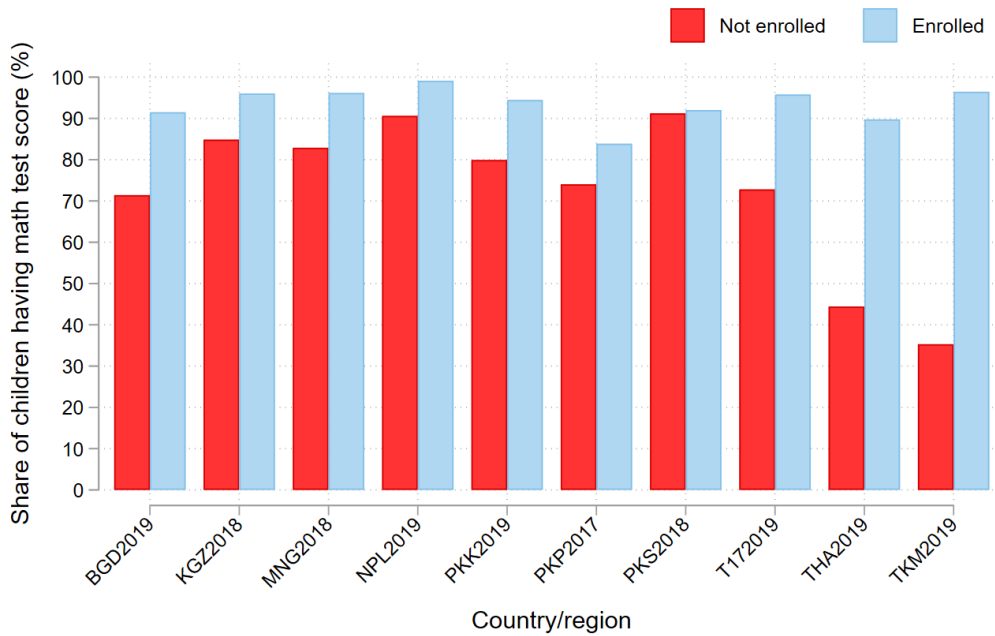
*Note:* Fractions show share of sample by age and country reporting math score, consistent share across ages, some variation across countries. We find much larger share with math-test scores reported if they are enrolled in school, all exceed 80 percent chance. Countries included are: Bangladesh (2019, **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)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure C.2: Reading Test Sample Size

(a) Reading Test Sample Size by Age
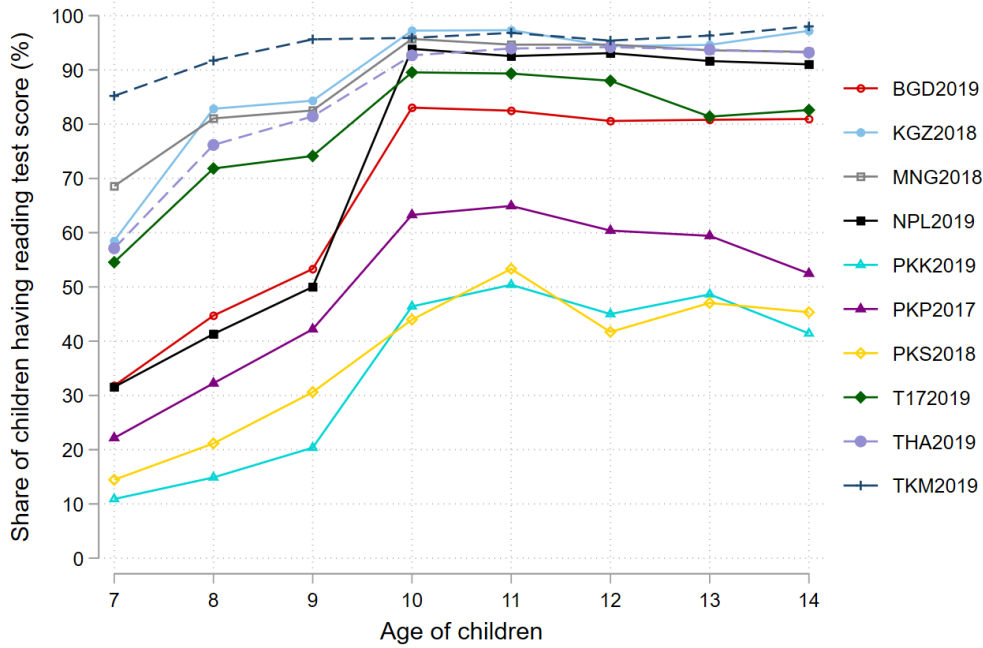
(b) Reading Test Sample Size by Enrollment Status Across Countries
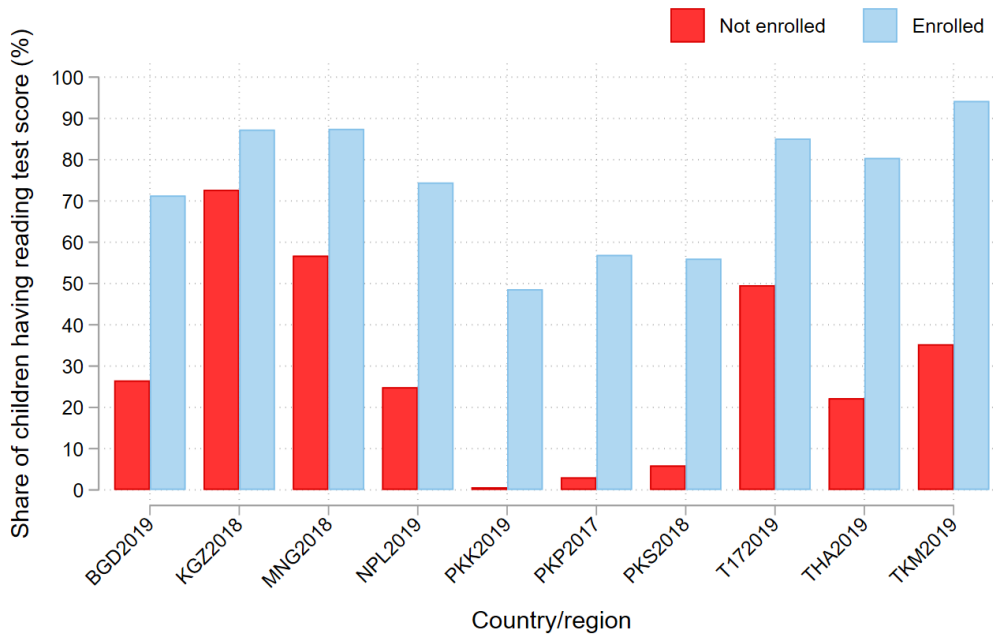
Note: Fractions show share of sample by age and country reporting reading test score, consistent share across ages, some variation across countries. We notice whether the child has reading test Score is related to if she is enrolled in school in the current period. We find much larger share with reading test scores if they are enrolled in school, all exceed 80 percent 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)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure C.3: Share of Children Whose Mother Has Some Education
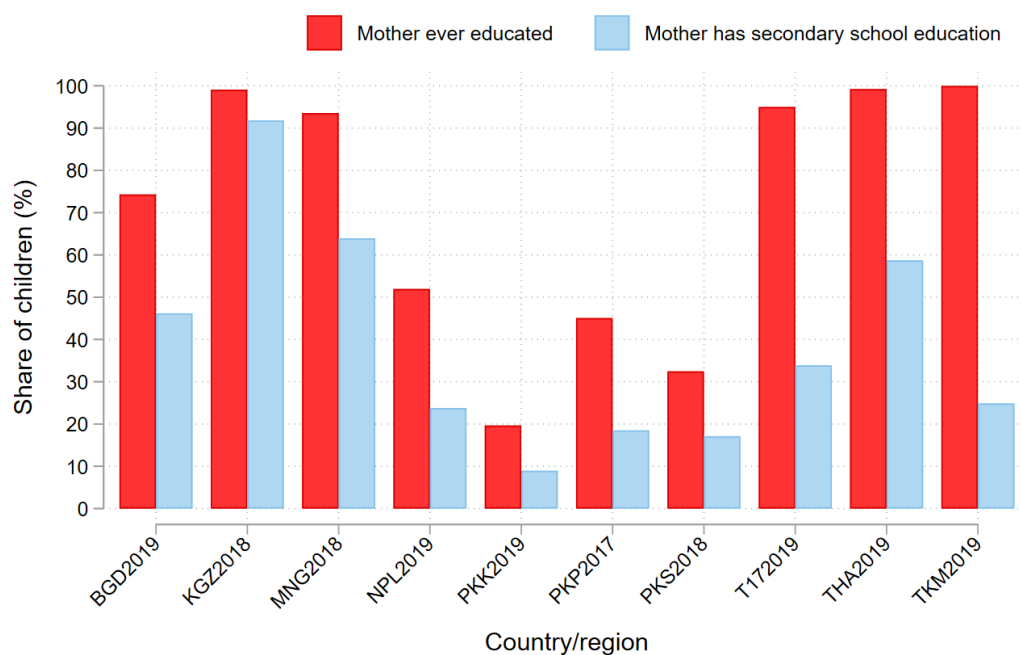
Note: This table show (1) share of children whose mother has had any kind of education (2) share of children whose mother has secondary school education by countries. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure C.4: Share of Children with Mother or Father Alive by Ages
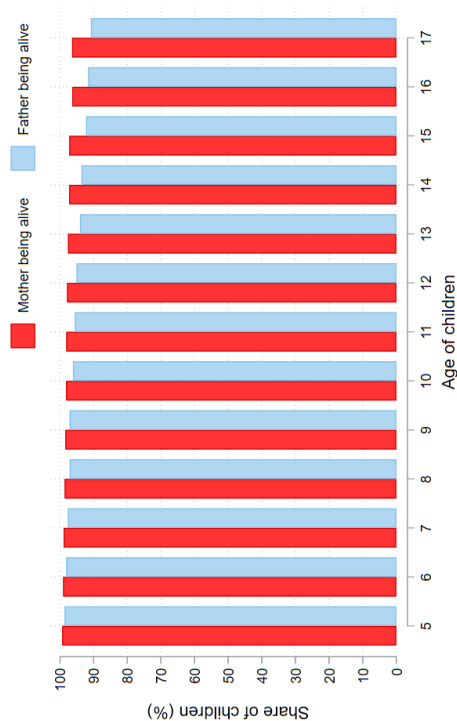
(a) Share of Children with Mother or Father Alive by Ages
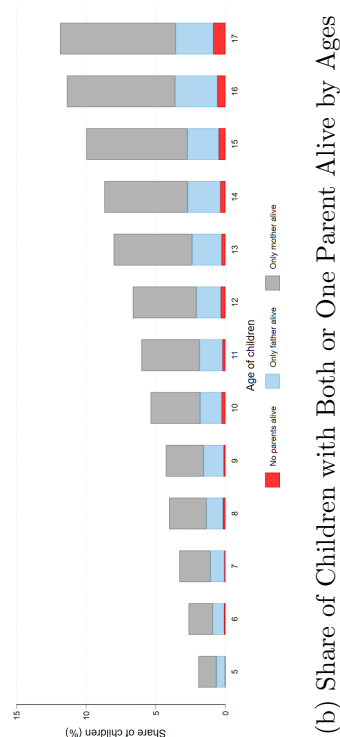
(b) Share of Children with Both or One Parent Alive by Ages

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

Note: Panel (a) shows the share of children with mother or father being alive by ages. Panel (b) and (c) show the share of children between 12-17, by ages or by countries, respectively, with both parents alive (not included in the bar), with just mother alive, with just father alive, with both parents not alive.

Figure C.5: Share of Children Living with Parents
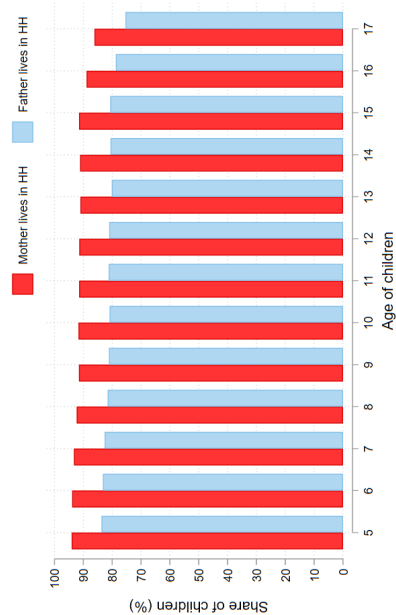
(a) Share of Children Living with Mother or Father by Ages
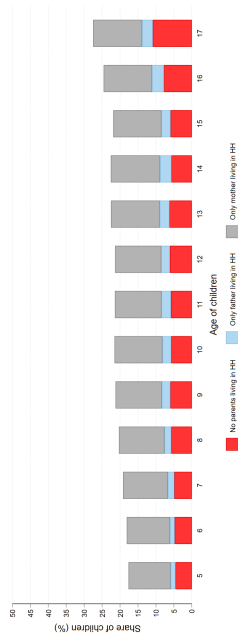
(b) Share of Children Living with Both or One Parent by Ages
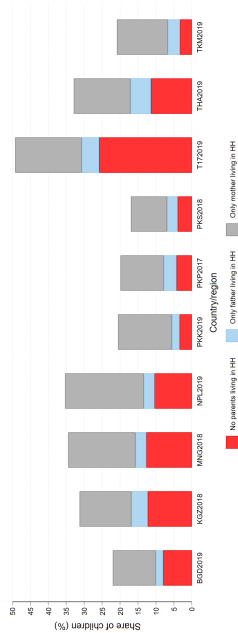
(c) Share of Children (Age ≥ 12) Living with Both or One Parent by Countries

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

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

(a) Progression Rate in Last Year by Ages and Countries
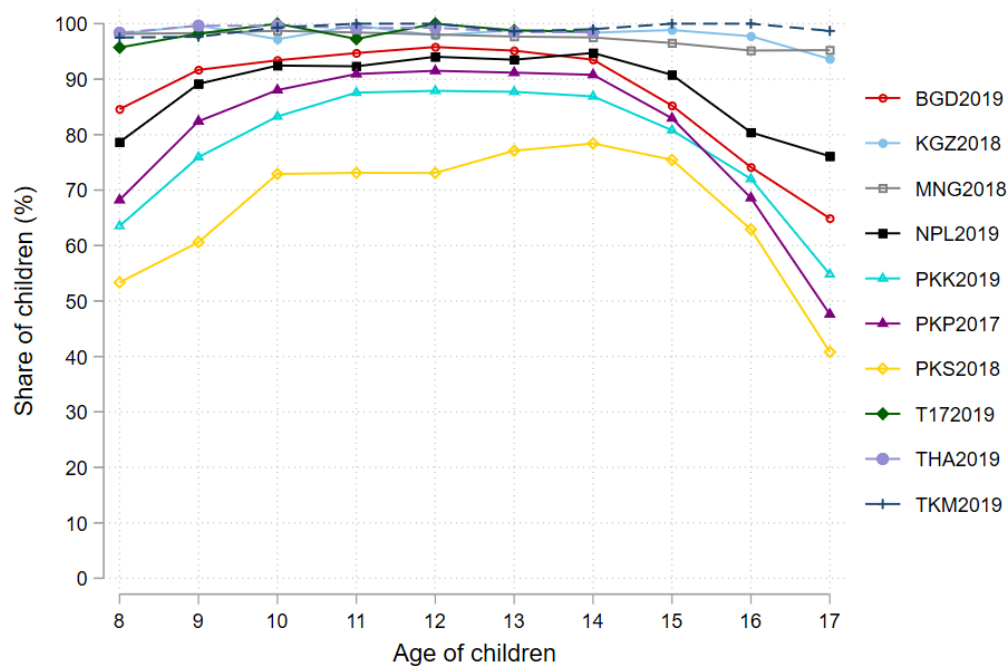
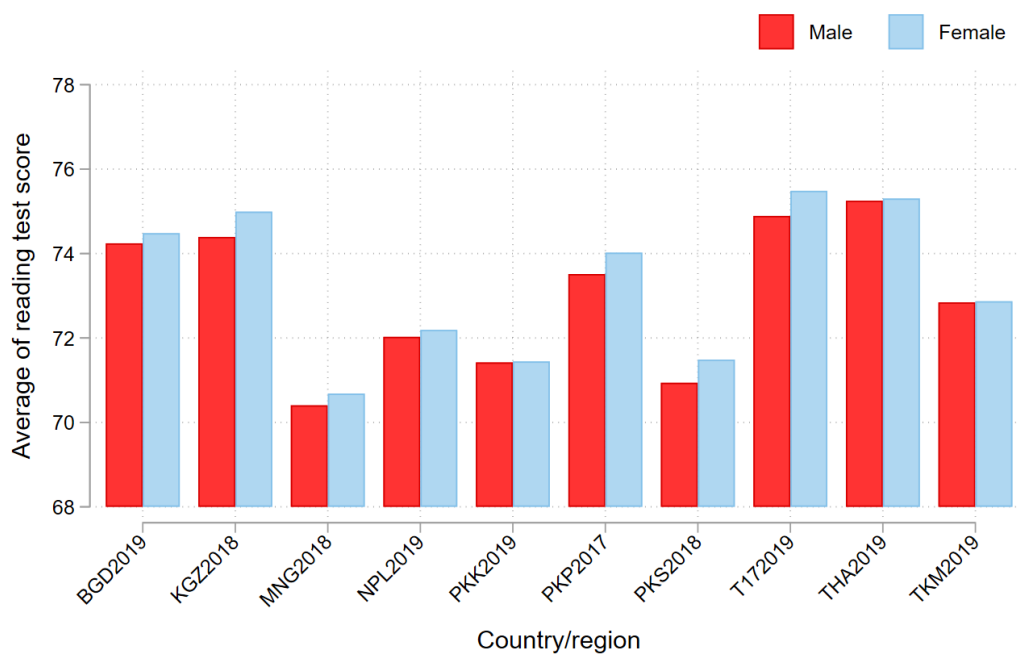(b) Progression Rate in Last Year by Gender and Countries ($\geq$ age 8)
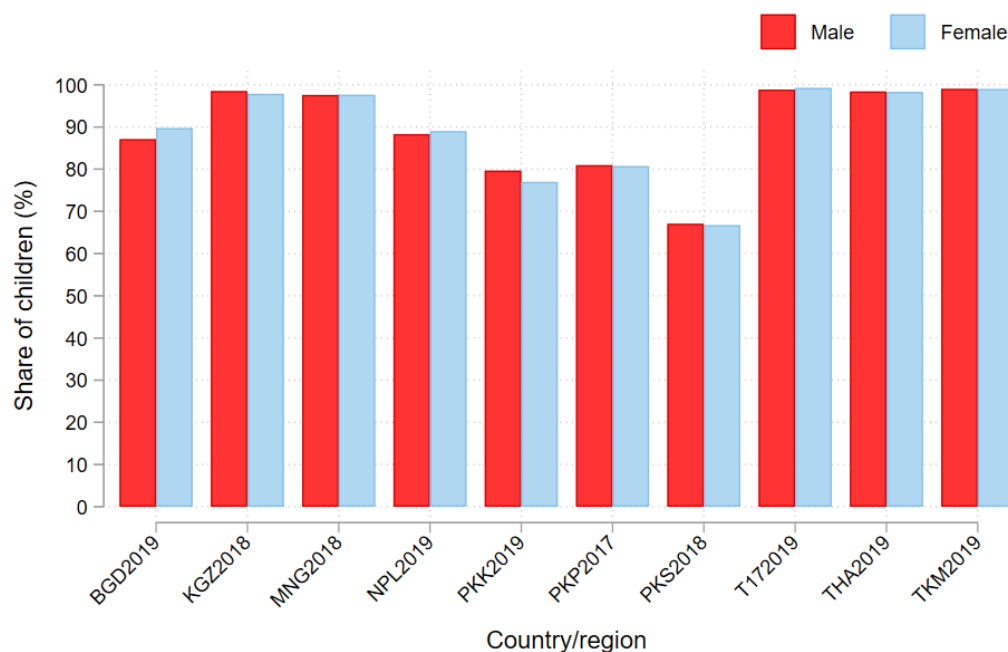
Note: The table shows progression rates. Progression is equal to 1 if a child attends a grade and successfully completes the grade, leading to an increase in grades completion by 1 years. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** for Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **TKM**).

Figure C.7: Distribution of Reading Test Score

(a) Average of Reading Test Score Across Ages and Countries
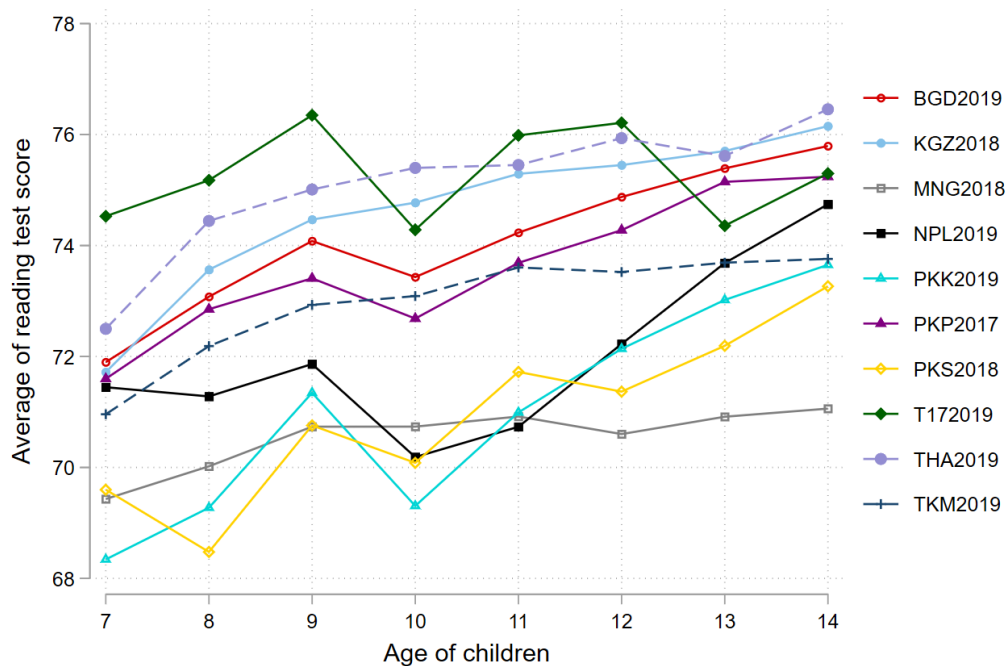
(b) Average of Reading Test Score by Gender and Countries (Age 7-14)

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)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **TKM**).