# Are Natural Disasters Disastrous for Learning? Evidence from Seven Asian Countries

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June 15, 2024

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**Abstract**

We estimate natural-disaster impacts on children's school enrollments and math skills and their age and gender heterogeneities in seven countries in the Asia-Pacific, the world's most disaster-prone region. We link survey data on children ages 5 to 17 to time- and geo-coded disaster variables. We create time-varying disaster exposures for each child for the first 1000 days after 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

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## 1 Introduction

The United Nations reports that between 1970 and 2019 climatic change and extreme weather caused a surge in natural disasters (United Nations 2021). Natural hazards accounted for 50 per cent of all disasters, 45 per cent of all reported deaths and 74 per cent 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 (Ipcc 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 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, not educational outcomes, 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). Infants' birth outcomes such as 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 tornados (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 exposure 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).

The relatively fewer studies on impacts of disasters on educational outcomes usually examine one disaster in one country rather than multiple types of disasters in multiple countries.[1] These 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 comes with high-intensity exposure to the 1976 Tangshan earthquake (Tian, Gong, and Zhai 2022), and a study revealing lower cognitive scores in chil-

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 United States and find that natural disasters affect a region's 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 of these studies focus on pregnancy and birth outcomes. Caruso (2017) studies all natural disasters in Latin America and investigates the effects on years of education, employment disabilities, unemployment, and wealth by type of disasters.

dren age 0-2 who experienced the 2006 Yogyakarta earthquake (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, 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 year of 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, we provide one of 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.[3] Specifically, we link individual level information on children ages 5 to 17 from seven developing countries in Asia from the Multiple Indicator Cluster Surveys (UNICEF 2010) together with time- and geo-coded disaster variables from the EM-DAT international disaster database (Mavhura and Aryal 2023; Guha-Sapir, Below, and Hoyois 2023). Given the countries and ages of children in the sample, we consider 509 natural disasters that have led to substantial loss of human life in these countries from 1998 to 2019 available from EM-DAT. These disasters include floods, storms, droughts, earthquakes, and extreme temperatures. Exploiting variations in MICS-

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

3. One closely related study is Caruso 2017, which examines the long-term effects of natural disasters in Latin America and inter-generational transmissions of early life exposures. It also focuses not on one single event, but various natural disasters. It studies human-capital outcomes in adulthood, such as years of schooling, employment disabilities, and wealth for the first generation, and enrollments, years of schooling, and child labor for the second generation. Our paper in contrast emphasizes educational outcomes of children directly exposed to the disasters and we focus on both enrollments and foundational learning outcomes assessed using MICS-administered math-test scores, which is a valuable measure of cognitive skill.

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 exposure histories for children surveyed in MICS in respective countries.[4]

We investigate the impacts of exposure history to natural disasters on human-capital accumulation. Short-term enrollment and cognitive-skills effects of disasters could lead to long-term impacts on human-capital development and accumulation. Therefore, We consider not only the impacts of recent disasters but also of early life disasters on human-capital accumulation. Children experience poorer health and educational outcomes in the long run if exposed to adverse prenatal and postnatal environments (Cunha et al. 2006; Heckman 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 impact 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 which is essential for cognitive development and performance (Almond, Edlund, and Palme 2009). Therefore we focus on the period from conception until age two (first 1000 days) to construct early life shocks.[5] Early life health abnormality could exert long term negative impact on IQ and cognitive development of children. This also increase the cost of these children attending schools compared to their healthy peers as they may need special education, more medical attention and miss classes more.

We estimate the impacts of natural disasters on school enrollment and human capital accumulation as measured by math skills for children in these countries. 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 exposure across time and within locations, the joint consideration of children's disaster exposure over their lifetimes allows the estimates from 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 history 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 augment an enrollment-decision equation that is a function of prior attainment, prior enrollment, and parental characteristics with children's recent and earlier disaster-exposure histories. To explore effects heterogeneity as moderated by permanent child- and household-specific factors, we allow for combinations of interactions between natural disasters and gender, age, and

4. In addition to considering all types of disasters, which is used to construct type-A disaster-exposure intensity, we also show results for considering only floods (type B), only severe disasters (type C), and only severe floods (type D). Severe disasters are defined as causing more than 50 deaths or injuries or affecting at least 5,000 people.

5. The first 1000 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; Maluccio et al. 2009; Victora et al. 2008; Victora et al. 2010; Hoddinott et al. 2013; Gertler et al. 2014; Black et al. 2022).

country while controlling for parental conditions. In our second empirical model, we specify an important indicator of learning—MICS-administered math-test scores—as the output of a human-capital-production function (Todd and Wolpin 2003; Hanushek and Rivkin 2012). Our unique child-disaster-history data 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 1000 days, time between the first 1000 days and most recent two years, and the most recent two years. To the best of our knowledge, this is the first paper to jointly consider the impacts of these correlated histories of disaster exposures.

We find significant negative effects of early life disaster exposures on enrollment status, but weaker or no corresponding effects related to recent-disaster exposures. Heterogeneity analysis shows that there is persistent negative relationship between early life natural disaster experience and enrollment through the primary-school-going ages for boys but not for girls. The association between exposures to natural disasters and math test scores is 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 disaster exposure, the cognitive performances( measured by math-test scores) of girls are harder hit than those of boys both in the younger and older cohorts (ages 7-9 and ages 13-14). Age patterns of learning effects of disaster exposures differ across national settings. 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 disaster 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-temporal reach. A group of studies for developing countries has 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 1990) and gendered differences in medical care and nutritional allocations (Alderman and Gertler 1997; Behrman 1988; Behrman and Deolalikar 1990; Gupta 1987). Our findings, on the other hand, 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 girls' long-term test scores and educational attainment but not boys'. Nübler et al. 2021 find that adolescent girls are affected more negatively 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 the 6th round of the Multiple Indicator Cluster Survey (MICS6) 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 the present, it has served as integral part of plans and policies of many governments covering 118 countries with 355 surveys containing more than 30 Sustainable Development Goals (SDGs) indicators. It 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 unit of analysis is the individual child. The household as well as 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. There is growing literature using MICS. They are a good resource for country- or sub-national level analysis. The recent rounds, for example, have been used to study the effects of COVID-19 school closures on cognitive skills in low- and lower-middle-income countries (Alban Conto et al. 2021; McCoy et al. 2021).

MICS6 provides information on school enrollments for children aged 5 to 17 and on foundational math learning of the subset of these children aged 7-14, which are our two dependent variables. MICS6 also provides information that we use as controls and to explore heterogeneities of the children (e.g., gender, ages, schooling attainment prior to the surveys) and of their households (parental ages and schooling attainments, household incomes). The data were downloaded from https://mics.unicef.org/surveys. In total, six model questionnaires are included in MICS6: Household Questionnaire, Water Quality Testing Questionnaire, Questionnaire for Individual Women, Questionnaire for Individual Men, Questionnaire for Children Age 5-17, Questionnaire for Children Under Five.

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 Asia and the Pacific (Mongolia 2018), Southeast Asia (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). The interview dates are recorded in MICS6, allowing us to match individual survey dates as well

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.

as the smallest unit of geo-identifier possible with the time- and geo-coded disasters for each location as well as individuals for our purpose.

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 and are geophysical, meteorological, hydrological, climatological, or biological (Mavhura and Aryal 2023; Guha-Sapir, Below, and Hoyois 2023). It is compiled from various sources: UN agencies, non-governmental organisations, insurance companies, research institutes, and press agencies. Disasters are recorded in the data if they meet any of the following inclusion criteria: (a) 10 or more people killed, (b) 100 or more people affected, (c) the declaration of a state of emergency, or (d) a call for international assistance (Panwar and Sen 2020; Mavhura and Aryal 2023; Sy et al. 2019). The coding of disasters is internationally standardized and allows researchers to link them with other databases such as the Dartmouth Flood Observatory, the Global Volcanism Program, and U.S. Geological Survey (USGS).

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 macroeconomic literature concludes that more than 60% of 64 primary studies published in 2000–2013 used EM-DAT (Lazzaroni and Bergeijk 2014). For example, it has been used to estimate the average outcomes in 73 nations (Kahn 2005), 89 countries (Skidmore and Toya 2002), 108 countries (Felbermayr and Gröschl 2014), and 109 countries (Noy 2009) over several decades. 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). Thanks to the recording of various types of disasters in EM-DAT, researchers are able to generally aggregate different disasters occurring in certain locations and time spans into a single index (Botzen, Deschenes, and Sanders 2019). For example, measures of disaster severity considering fatality counts above certain thresholds are constructed from EM-DAT or ARC records for a study at county-level in the U.S. and there are 151 disasters with 25 or more deaths constituting 1.5 percent of all events in the U.S. from 1930 to 2010 (Boustan et al. 2020).

Available disaster-related variables can be categorized into two groups: context variables and impact variables. Context variables provide geographical and temporal information of each disaster. For geographical information, country, region, continent, and river basin are considered. Administrative level codes and location names of all locations affected by this disaster are also listed, which are the crucial variables that we use in this project to link individuals' locations. The administrative level and location sizes vary by country. For example, in Bangladesh, we know which district each individual is living in. Districts are the second-level administrative divisions in Bangladesh, with populations ranging from over 14,700,000 in Dhaka to under 700,000 in places like Rangamati. Temporal information includes start date, end date, and local time. There are also physical characteristics such as origins, associated disasters 1 and 2, disaster magnitude scales and values. Aid contributions, Office of US Foreign Disaster Assistance (OFDA) responses, appeals for international assistance and declaration are offered as disaster status. Impact variables assess the severity of each disaster. EM-DAT encompasses health impact data, including statistics on deaths, missing persons, injuries, affected individuals, and those rendered homeless due to disasters. Total estimated damages, reconstruction cost and insured losses are additionally included as economic-impact information.

## 2.3 Measures

### 2.3.1 Parental and Household Characteristics

For socioeconomic status (SES), we consider parents' ages, educational levels, whether parents are alive, and whether parents are co-resident with the child. MICS surveyed every woman and man in the selected households who were in the age range of 15 to 49, but collects some major information about every household member. We match the biological mother and father for each child and obtain their demographic information We construct two measures for educational level for parents: one indicator for ever attending school, and a second indicator of having secondary schooling.

### 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 rate at the regional level[8] for each country in Table 1. Math skills are assessed for children aged 7 to 14 years old by tests administered in the survey. Since these tests are administered at the children's homes, our analysis is not subject to selection bias due to school enrollment or attendance. 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 math test includes scores on recognizing symbols, comparing numbers, numbers adding up, and identifying the next number.

### 2.3.3 Disaster Shocks

**Binary and Continuous Measures of Disaster Intensity in Particular Time Spans.** We assume children do not move and reside since conception in the current location recorded in MICS. The migration history of children is not observed. Nevertheless, 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 of duration having lived in current location, and prior location which can be recorded at a different administrative level. [9]

7. We provide more details on measures construction in the Online Appendix section. MICS has reading tests as well, but the 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 locatios 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 at the first administrative level which is much larger. For Thailand, there is also finer information for current locations of mothers (region and changwat), but only region names for prior locations. For Turkmenistan, first-level administrative (region or province) location names are collected for current and prior locations of mothers.

Within 144,471 children in our full sample, 101,435 (70%) are merged, meaning that their mothers have been surveyed individually. 43,036 (30%) cannot be merged with any woman aged 15-49, and 45,952 (32%) do not have information on how many years the mother has been living in the current place. There are several reasons mothers' migration information may not be available. First, the Pakistan Khyber Pakhtunkhwa Province (denoted as "PKK") women file does not contain migration variables. Second, only women aged 15-49 are surveyed separately. The natural mothers of children in the sample may be older and not included in the women module. 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 that we do have some migration information from, as shown in Table C.3, the vast majority have had the same location since child birth, and even among those who moved, our location history is largely correct for most of their lives.

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 one flood is recorded as having affected Chittagong Division in EM-DAT, then children in Chandpur District are assumed to be exposed to this flood. Then, by using starting year and month, ending year and month of each disaster, interview dates and ages of children in MICS data, we match the disaster to each child in each month and location. We first construct the binary indicator of disaster for each child in each month, $DI^p_{il,mo}$. It is one if location $l$ in month $mo$ has experienced the type $p$ intensity of disaster shock and zero otherwise (see below for the definition of intensity types). For child $i$ who currently lives in that location $l$, we assign this disaster shock intensity to her. If one disaster occurring in month $mo$ lasts for less than one month, $DI^p_{il,mo}$ is counted as one as well. Then, by calculating $DM^p_{il,j}$, the number of months child $i$ in location $l$ during the span of time $j$ experienced disasters, we are able to obtain the binary indicator for existence in time span $j$ of type $p$ disaster intensity, which is denoted by $DB^p_{il,j}$.

$$\begin{aligned} DM^p_{il,j} &= \sum_{\text{mo=start mo. of j}}^{\text{end mo. of j}} DI^p_{il,mo} \\ DB^p_{il,j} &= 1\{DM^p_{il,j} \geq 1\} \end{aligned} \tag{1}$$

**Critical Life-Cycle Periods.** We focus on critical life-cycle periods for which to construct the individual-specific particular time spans. These include the most recent year prior to the survey month (including survey month), the year before the most recent year, the first 1000 days (early life), and the time between early life and the two years prior to the survey month.

This is feasible as interview years and months and birth years and months are available for all children in our MICS sample.[10] The earliest year of birth for a child in these samples was

10. In fact, interview dates are observed for all children as well, but we choose to construct the disaster shocks at the monthly level because birth days are not observed for all children and starting (birth years and months are observed), and ending years and months (not days) of disasters generally are not recorded, making it difficult to match disasters with individuals' life cycles at the day level.

1999. When we track the EM-DAT disasters from 1998 to 2019, there are in total 509 disasters that happened in that period. All but three events have information on start years and start months, yet 86 disasters are not recorded with start days. The end years of all disasters are observed with end months of only ten disasters missing, but end days of 87 disasters are missing.

**Disaster-Intensity Type.** For the disaster-intensity type denoted 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 50 deaths or injuries or affecting 5,000 people or more. Type D combines B and C to consider only severe floods. In the main results, we use type A disaster intensity for all time spans. Having various types of disaster intensities provides us the possibility for robustness checks on disaster experience construction, which we explore in Appendix C.

# 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 MICS sixth-round 5-to-17 years-of-age module. Some important points are noteworthy about the MICS data. The data provides information on enrollment, and foundational-math-learning-assessment-test scores for these children. However, the sample sizes differ for enrollments versus math-test scores because only children aged 7 to 14 years participated in the foundational-learning-assessment module (subject to their availability at home and parental consent during the survey). In Table 1, we show that the whole sample was collected between 2017 and 2019. Each country is associated with geo-identifiers at the smallest administrative levels possible, but these differ across countries. 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 of all variables in three panels. The total sample includes 144,471 children, with 48% being female. We present the distributions of the samples by country and age in Figure 1. The average enrollment rate in the school year when children are surveyed is 90%, though the average enrollment rate in the previous year is lower. 90% of the children have math-test scores.

### 3.1.2 Parental and Household Characteristics

Table 2 shows that fathers' ages are on average 6 years greater than mothers' ages, and the percentage of father ever-educated is slightly higher than that of mothers. But it is also noticeable that father information is collected for a smaller sub-sample than that of mothers. We find larger shares of children with mothers living in the same household than fathers, and more children with mothers who are alive. In Figure 2, we present 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 across countries. In Turkmenistan, Kyrgyzstan, Thailand, and Mongolia, the share of mothers who have been ever-enrolled is larger than 95 percent; In contrast, in Bangladesh and the three provinces of Pakistan, the shares are 74 and 36 percent, respectively.[11] In Kyrgyzstan, the shares of mothers with higher than middle-school education and ever-enrolled are both higher than 90 percent, but in all other countries, the shares of mothers with higher than middle-school education are equal to half of the shares of mothers who have ever been enrolled in school.

#### 3.1.3 Educational Outcomes

In Panel 1 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 outcomes by countries. We find that among the countries we study, children in Pakistan have the lowest enrollments and attainment, followed by Bangladesh. 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.

**Enrollment.** In Figure 3, we present enrollment status in the survey year. Girls' current enrollments compared to boys' are higher in Bangladesh compared to most countries and lowest in the Pakistan provinces. Enrollments in the current year as well as the preceding year 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 up to about 30 percent of children are never enrolled by age 17 years in Sindh Province.

**Educational Attainment.** Educational attainment is defined as the highest completed grade by a child at the child's current age at the time of the survey. Results on attainment by age and country are shown in Figure 6. Average maximum 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 in grades of schooling. We note the average maximum attainment is higher for girls compared to boys in Bangladesh, Nepal and Thailand and its lowest for children in Pakistan. For children 15-17 years of age, girls outperform boys in Bangladesh, Kyrgyzstan, and Mongolia.

**Test Scores.** Average math-skill-test results by age and country are shown in Table 3 and Figures 8. Aggregate math scores differ substantially across countries with children in Bangladesh

11. According to a report on Pakistan from DHS (National Institute of Population Studies and ICF 2019), half of ever-married women aged 15-49 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.

and Pakistan performing the worst. Girls slightly outperform boys in Bangladesh, Kyrgyzstan, Mongolia and Thailand; boys slightly out perform girls in Nepal, Pakistan and Thailand.

Given the uniform test administered to children of all ages, not surprisingly, older children perform relatively better than younger children. As shown in Figure 8, for the math test, children from Turkmenistan, Kyrgyzstan, and Thailand have relatively high average scores across age groups. Children from Nepal and Bangladesh have medium levels of average performances and sharper increases in math-test scores 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 in the 12 months previous to the interview months, in total, 55% of children in the seven countries experienced at least one disaster. The average share of children experiencing any disasters in the 10 years prior to most recent year is 77%, more than three fourths of locations in our sample.

In Table 4, furthermore, we show variations in disaster exposures across countries. For example, in Bangladesh, 88% of children experienced disasters in the previous 12 months.

Additionally, we show in Figure 9 the shares of location/months experiencing disasters of different types by calendar months and locations. The results show more location/months with disasters during the summer months.

## 4 Estimation Strategy

Given variations across geo-identifiers and survey dates (see Table 1), we aim to identify the effects of disaster exposures on children's educational outcomes by jointly exploiting temporal variations in disaster exposures within the same location as well as intensity variations in disaster exposures across locations at the same time.

We study the heterogeneous impacts of natural disasters on school enrollments and math-test performance for children along gender, age, and SES gradients. We model educational outcomes as a function of natural disaster shocks with household and child characteristics as controls. To explore effects heterogeneity as moderated by permanent child- and household-specific factors, we also estimate the model allowing for combinations of interactions between natural disasters and gender, age, and country.

We employ several models to estimate the impact of local-level natural disaster shocks on individual-level enrollments and math-test scores (each is denoted by $E$ and $S$, respectively, in the following sections).

Note that a key aspect of our estimation strategy is to exploit heterogeneities in the timing of survey months and child ages within sub-national locations. Specifically, we use $t$ to denote the school year a child is in when taking the survey, $m$ to denote the interview calendar month (i.e. the difference between current month and January 1900), $j$ for location or individual-specific span of time of exposure, and $g$ for age in months of the child in the interview month. For example, if the child is born in January 2000, and is interviewed in January 2017, then she is $g = 17 * 12$ months old in the interview month and $g - 12$ denotes the age in months at the start of the most recent year before the interview month.

**Enrollment and Exposure Histories 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, the child cannot complete additional grades; with enrollment, the child has some probability of passing the grade and thereby increasing her educational attainment (Attanasio, Meghir, and Santiago 2012). The gains from enrollment come from the expected value of increases in educational attainment and achievement by the start of the next school year; the costs of enrollment include the pecuniary and non-pecuniary, direct and opportunity costs of going to school in the current period (Todd and Wolpin 2006).

In the current period, decision makers might consider jointly as key state variables the existing levels of educational attainment (grades completed), prior enrollment decisions (potential difficulty with re-enrollment after dropout), and the age of the child. These factors jointly determine the benefits and chances of school progression. Additionally, decision makers also consider potentially two types of shocks. The first type of shocks are realized shocks known to parents at the time of making enrollment decisions, and these generate random variations in the relative gains and losses from enrollment. The second type of shocks are realized after the enrollment decision is made and during the process of attending schools. The probabilities of experiencing these yet-to-be-realized shocks could impact the chances of progression and hence the parents' decisions for enrollments.

In this paper, we estimate a reduced-form model of enrollment decisions as a function of child age, prior attainment, prior enrollment, and disaster shocks. Based on the EM-DAT disaster data, which we match based on location and timing to children and observed decisions to enroll, we can estimate the effects of disasters on the enrollment decisions.

First, we consider recent 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. It is important to note that because we do not have complete information on exactly when parents are making enrollment decisions, some of the disaster shocks might have impacted the enrollment decision, and other disaster shocks that arrived later might not impact enrollment but mainly impact attendance or progression. Our estimation strategy is based on the demand side conditional on local-market conditions. We assume that within the same location, the difference in children's enrollment status and attainment comes from individual cognitive skills and progression, which come in part from variation in disaster exposure histories.

The variability we estimate does not come from differences in the partial-equilibrium local markets because we have location-level fixed effects.

Second, we also consider early childhood as the experience during early childhood has been found to be related to 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). Disaster shocks exposures in early childhood might have had formative impacts on the cognitive and non-cognitive skills as well as the health status of the child. These underlying characteristics of the child, which cannot be fully captured by prior attainment and prior enrollment, might impact the expected gains from additional years of schooling and the possibility of success with progression. While these characteristics are not observed in our data by the econometrician, parents might take these into consideration in making enrollment decisions, creating a channel for early life shocks to impact enrollment decisions.

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

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

where TimeSpan $= \{m12to1, first1000days\}$ with $m12t1$ representing the most recent year up to the survey month and $first1000days$ capturing the first 1000 days. $E_{il,t-1}$ is enrollment status of child $i$ living in location $l$ at start of last school year $t-1$. $A_{ilt}$ is grade completed by the end of period $t-1$ and at the start of period $t$. $D_{ilj}^p$ denotes the natural disaster shock of type $p$receved by child $i$ in location $l$ at time $t$, looking back at prior time span $j$.

$D_{il,m12to1}^p$ captures the disaster-shock-exposure intensity during the current school year, jointly with $E_{il,t-1}$, $A_{ilt}$, and $E_{il,t}$ describes the yearly enrollment decision process. $D_{il,first1000days}^p$ is included to denote the initial early life shock received and we allow for this initial shock to have continued effects on enrollment status through both $\beta_{m12to1}$ and $\beta_{first1000days}$. By incorporating the initial shock into the estimation equation, we allow for the possibility of heterogeneous, non-proportional initial effects on the current enrollment status $E_{il,t}$. Our underlying assumption is that, over time (as $t$ increases), there are cumulative effects from the histories of shocks, with the initial shock being given greater weight. In this setting, a negative coefficient $\beta_{first1000days}$ in the regression results would imply that the estimated effects are a lower bound of the true effects as part of them are reflected in the influence of the previous year's enrollment status on the current enrollment status.[12]

We control for a vector $X$ of observed individual and parental characteristics including parental ages, mothers' education, whether the child resides with parents, and whether parents

12. If the first 1000 days shock is not included, the assumption would be the lagged enrollment variables are sufficient statistics for all previous shocks.

are alive.[13] Additionally, we control for sub-national location fixed effects $\mu_l$, 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, $\mu_t$.[14]

Controlling for these fixed effects and observed characteristics is critical for capturing the causal effects of disasters on enrollments. While disasters are not choices made by parents, the distribution 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 across children within location $l$ given different experiences of disasters due to within-location survey month heterogeneities and within-location child-age heterogeneity: 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 year- and 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 functions (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 scores at different ages, and inputs from different stages of a child's life might have heterogeneous effects on the achievement score at a particular age (Todd and Wolpin 2003).

In many empirical settings, it is difficult to obtain the full history of inputs, so researchers sometimes rely on strategies with panel data 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 that we constructed with the EM-DAT disaster dataset. Our strategy is to estimate the effects of past disasters on achievement by including the full history of disasters, this allows us to estimate the heterogeneous effects of disasters from different stages of a child's life-cycle.

In contrast to child, family, school, and neighborhood inputs, we assume that disasters are not endogenous choices made by parents or children. Nevertheless, the child, the family, the school, and the neighborhood, can all respond endogenously to disaster shocks by changing their inputs for the child's human-capital-production function. 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 relationship between the life cycle of EM-DAT disaster exposures and MICS-administered

13. The fathers-above-middle-school-or-not variable is observed for a more selected sample, hence we rely mainly on mothers-middle-school-or-not variable.

14. We control for survey year × month fixed effects, for notational simplicity, $t$ only denotes the survey year. We consider in the estimation the survey timing by survey month, specifically, we use interview calendar month, i.e. the difference between current survey month and January 1900.

achievement tests using the following specification:

$$S_{ilm} = \alpha + \sum_{j \in TimeSpan} \beta^p_j \cdot D^p_{ilj} + \theta X'_i + \mu_{c,A_i(m)} + \mu_l + \mu_{g_i(m)} + \mu_m + \epsilon_{ilm} \ , \tag{3}$$

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 three parts, TimeSpan $= \{m1to12, m13to24, midchildlife, first1000days\}$, which contains 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 1000 days (a span that we define as mid-child life), and the first 1000 days. We compare test scores, controlling for location fixed effects, $\mu_l$, survey-timing fixed effects, $\mu_m$, child-age fixed effects, $\mu_{g_i(m)}$, and country- and attainment-specific fixed effects, $\mu_{c,A_i(m)}$.

When estimating Eq. (3) for children from all ages jointly, we implicitly assume that the differing effects of early, mid-life, as well as 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 $\beta^j_{g_i(m)}$:

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

where $\beta^j_{g_i(m)}$ is specific to child age $g_i(m)$ which is a child-specific function based on child birth date and current survey month.

Our estimation strategy exploits heterogeneities in disaster histories within locations and across individuals. In practice, because conditional on location and age jointly, there are no variations in child exposure histories, we cannot estimate Eq. (4) with separate $\beta^j_{g(i,m)}$ for each age. 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), with the assumption that the effects of disaster histories are homogeneous within each age group.

# 5 Results

## 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 had a disaster in the most recent 12 months before the survey month as well as the number of months a child experienced disasters in the first 1000 days on enrollment in the current school year during which the child was surveyed. In column one of Table 5, we consider only lagged enrollment and grades completed at the start of the current school year as controls. In column two, we add in controls for child, parental, and household characteristics including child being female, mother or father being alive as well as living in same household with child, mother ever-schooled and if mother has secondary schooling. We then add in a battery of additional variables in column three for location, calendar time, and child-age fixed effects.

Averaging across children between ages 5 and 17 and from all the countries that we study, we find a significant negative effect of early life disaster-exposure experience on enrollments, but no significant relationship between experiencing EM-DAT disaster in the most recent year and enrollments. The magnitude of the early shock effects are dampened by about half with the inclusion of fixed effects, but remain strongly significant. Specifically, in column three, we find that each additional month in the first 1000 days exposed to EM-DAT disaster reduces enrollment by 0.1 percentage points. There is significant heterogeneity in the number of months exposed to early life disasters across and within countries, with an overall P10 to P90 range of 0 to 8 months of early life disaster exposures (with an average of 3.0 months and a standard deviation of 3.7 months), which correspond to a slightly less than 1 percentage point reduction in enrollments between p10 to p90 exposures to early life disasters on school enrollments.

Following our discussions of the enrollment decision model, in all columns of Table 5, we include lagged enrollments from the prior school year (enrollment in year $t-1$) as well as attainment (grades of schooling) completed at the start of the current school year (at the start of $t$). We find strong positive associations between both and current enrollments. On average, those enrolled in the last school year are about 64 percentage points more likely to be enrolled in this year, and each year of additional existing grades completed increases enrollment by about 2.4 percentage points. Even after controlling for lagged enrollments as well as attainment by age and country fixed effects, there is still strong and positive effects of lagged enrollments on current enrollments.

We also find consistent patterns of relationships between child, parental, and household characteristics and enrollments from columns 2 and 3 of Table 5. Specifically, from column three, aggregating across countries and ages, we find girls have 0.6% lower enrollments than boys. We also find that having a mother who has had any prior schooling is associated with higher enrollments by 4.1%, and having a mother with secondary schooling is associated with higher enrollments by an additional 1.1%. Interestingly, we find that having a mother who is living in the same household is associated with increased enrollments by 2.5%. In contrast, having a father living in the same household is associated with a 0.7% increase in enrollment, but having a father alive but not living with the household is associated with a larger increase in enrollments by 1.2%.

In Table 5, we consider all kinds of disasters regardless of their categories or severity. Table C.10 additionally shows results using other measures of disaster intensity for estimating the effects of disaster exposures on enrollments. Each column corresponds with one disaster intensity type described in 2.2. Column (2) shows that having experienced any flood in the most recent year prior to the survey/test decreases the probability of children going to school by 1.2 percentage points. However, this effect becomes insignificant if we only consider severe disasters (column (3)) or severe floods (column (4)). Considering only floods or severe disasters doubles the magnitude of the estimated effects of early life exposure on enrollments compared to all kinds of disasters.

### 5.2 Heterogeneous Effects on Enrollments Across Ages, Genders, and Countries

Table 5 presents the average effects of disaster experiences on enrollments in the current year for all children between ages 5 to 17 and across all countries. Enrollment patterns across countries as shown in Figure 3 differ substantially across ages, gender and countries. In this section, we continue to estimate Eq. (2) using linear probability models by regressing enrollments in the survey years on disaster experiences, but explore heterogeneity by child-age groups in Table 6 and heterogeneity by joint child age and gender in Table 7. The heterogeneity by gender is presented in Table C.6 and we further present heterogeneity by joint child age and country groups in Table C.5.

In both Tables 6 and 7, we present results in two columns. The first column includes the same set of controls and fixed effects as column three in Table 5. In column two, we replace the sub-national MICS-survey-lowest-administrative-level fixed effects by MICS-survey-cluster fixed effects. There are about 250 sub-national MICS locations with heterogeneities in aggregation level across countries as shown in Table 1. In contrast, there are about 11000 clusters with similar sample sizes in each.[15] Within each cluster, there are variations in child ages and some limited variations in survey months. In the second column of Tables 6 and 7, we exploit child-age variations within each cluster and within each of the three age groups (5 to 8, 9 to 12, and 13 to 17) to identify the effects of early shocks, and we exploit variations in survey months within clusters to identify the effects of recent shocks. Age groupings are defined based on the age range for primary-school education across different countries. 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, elementary school encompasses children aged 6-12. In Turkmenistan, the official primary-school entrance age is 6 and the primary-school cycle lasts 4 years. Hence, we designate age groups as 5-8 for lower grades and 9-12 for upper grades of primary school. For post-primary through high school, we use the age group 13-17.

Overall, we find persistent negative impacts from early life disaster experiences on enrollments throughout school-going ages especially for years in primary school. We also find that the effects of recent and first-1000-days disaster shocks have different profiles of life-cycle impacts across genders.

In Table 6, focusing on the results with within-country location fixed effects, we find that experiencing disaster in the most recent year has close to zero effect on enrollments for all ages. Children aged 9-12 are more vulnerable in terms of staying enrolled in school if they are hit by natural disasters in early life.

Gender plays an important role on educational outcomes in the countries we consider in this study for multiple reasons. One example is that some areas in Pakistan favor male children for educational-resource rationing (Raza, Shah, and Haq 2022). A study on a locust plague in Mali shows that school enrollments are reduced by 2.8 percentage points by exposure to the natural disaster of boys born at the time of the shock, while girls are found to have negative impact purely on attainment measured by grades of schooling (De Vreyer, Guilbert, and Mesple-Somps 2015). As shown in Table 7, we also find that boys are affected more than girls by early life disaster shocks. By interacting disaster shocks with age groups and gender,

15. Each cluster includes a range of from 1 to 23 sampled household (one child is selected from each household). On average, 6 households are surveyed in one cluster. We map the MICS sub-national locations to EM-DAT reported disasters, which are also measured at sub-national aggregate levels. We do not know the geographical coordinates for each cluster and do not have cluster-specific disaster information.

we find that having experienced any type of disaster in the most recent year implies higher probability of going to school for both boys and girls. It is plausible that in some settings, schools might be safe and resourceful locations for children during times of disasters due to the ease of coordinated and centralized disaster-relief efforts. In the enrollment-decision problem, parents consider trade-offs between going to school and staying at home. It is plausible that in some empirical settings and for some age groups, disasters worsen conditions at homes more than at schools, and consequently, through parental initiatives and governmental encouragement, locations experiencing disasters might see increased enrollments post disasters. As children age, the effects of early life disaster exposures on enrollments appears to be strongly significant negative, especially for boys. Boys aged 9-12 experiencing one additional month of disaster exposure in the first 1000 days are about 0.3 percentage points more likely to be not enrolled, while no similar impact is shown for girls in the same age range. Considering the disaster shock not only affects individuals but also creates potentially long-run negative income shocks to the families, it is plausible that older children tend to drop out of school and help with housework and boys may be more likely required to do so at younger ages. However, we do not know when they drop out in our sample.

In Table C.5, we present separate estimates for children in the three age groups from Pakistan, Bangladesh and other countries. In Pakistan, we find weakly negative impacts from recent disaster experiences on enrollments in all three age groups. For early life disaster experiences, we find a strongly significant negative impact of early life disaster exposures on enrollments between ages 5 to 8, but not in older ages. Specifically, one month of additional disaster exposure in the first 1000 days reduces enrollments by 0.6 percentage points in children between ages 5 to 8 in Pakistan. As discussed prior and shown in Figures 4 and 3, the Pakistan samples have the lowest enrollments.

In Bangladesh, we find for both recent and early disaster exposures a sharp age gradient, with growing negative effects of disaster on enrollment as children age. Considering the results with within-country-location fixed effects, early life disaster experiences are found to be unrelated to enrollments for children between ages 9 to 12 but not the recent experiences. In contrast, between ages 13 to 17, having experienced disasters in the past year reduces enrollments by 2.7 percentage points, and having an additional month of early exposure reduces enrollments by 0.3 percentage point. For children between ages 5 to 8, we find significant positive impacts in Bangladesh on enrollments from recent shocks.

Results for heterogeneous effects of disaster exposures on enrollments using other types of intensity are shown in Table C.11 and Table C.12. Breaking down the effects by age groups, all disaster-intensity types present significant negative effects from early life shocks on enrollment, with a more persistent negative relationships between early exposures and enrollments through school-going ages. When only floods are considered, children experiencing disaster shocks in the previous years prior to survey months are less likely to be enrolled. In C.12, boys are found to be affected more heavily and negatively by recent disaster exposures than girls after age 8 along all intensity types. Meanwhile, children of both genders are observed to have lower enrollment rates by about 0.3 percentage point if they have experienced one more month with only floods, only severe disasters, or severe floods.

### 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.[16] In columns one and two, we estimate with various fixed effects but without individual-specific controls, which are included in columns three and four. In columns one and three, we use the MICS sub-national location fixed effects, and in columns two and four, we use MICS country-specific cluster fixed effects. Coefficients are in scales of the MICS math-test scores (see Figure 8 which shows the average math-test score by ages, gender and countries), which varies between 0 and 21 points.

In all columns of Tables 8, we find consistent results of weak and insignificant effects of recent disasters on math scores, but significant effects of disasters in the first 1000 days on test scores. The estimates with demographic controls suggest impacts of having disaster shocks in the first 1000 days on math-test scores of 3 percentage points. Focusing on estimates from column (3) using MICS sub-national location fixed effects, we find that, averaging across children between 7 and 14 years of age and from all countries, each additional month of early life disaster exposures reduces test scores strongly significantly by 3.1 percentage points. Estimates from column (4) using MICS-cluster fixed effects show similar findings with slightly smaller magnitudes of impacts.

We also find consistent patterns of relationships between child, parental, and household characteristics and enrollments from columns (3) and (4) of Table 8. Girls are found to have lower scores than boys holding other factors constant. We also find that having a mother who has had any prior schooling 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. In contrast, having a father who is alive but not living with the household is associated with higher test scores.

The estimated average effects of disaster exposures on math skills using other disaster intensity types are shown in C.13. There are no significant effects from disaster exposures in early life if we only investigate severe disasters. However, there remain consistent and negative effects from early life exposures to floods. Having one more month experiencing floods in the first 1000 days indicates a 6.5 percentage point decrease in math-test scores.

### 5.4 Heterogeneous Effects on Math Skills Across Ages, Genders, and Countries

Given the substantial variations in math-test scores across age groups and countries shown in Figure 8 and following Eq. (4), in Tables 9, 10, and 11, we estimate heterogeneous effects of life-cycle disasters on math scores conditional on gender and age groups separately and jointly. Heterogeneity across country settings is shown in C.8 and C.9. Although effects of disaster shocks in recent years, mid-child life, and early life are all estimated, we only present those of early life and mid-child life disaster experiences because the effects of recent disaster shocks remain insignificant in all regression results.

Similar to Tables 6 and 7, we present results in two columns, where the first column

16. As discussed in the data section, while we also have reading scores, those are observed in a much more selected way, so we focus our analysis on math scores. See Figure C.1 for the sample structure for math scores, and Figure C.2 for the sample structure for reading scores.

uses MICS sub-national fixed effects and the second column controls for MICS cluster fixed effects. Different age grouping is used for estimating the effects of disaster shocks on math scores as only children aged 7-14 are given the tests. We group children based on the usual age of entering secondary school (10-12). In Table 9, we find weakly negative effects of early disasters on test scores for children ages 7 to 9, with magnitudes of estimates being broadly similar to average estimates considering all ages from Table 8, but the standard errors now are larger. In our results from heterogeneous analysis across genders, it is noticeable that there is a greater impact of early life exposure to natural disasters on girls' math-test performances than on boys'. On average for girls aged 7 to 14 years, one more month with disasters in early life reduces the math-test score by 0.034 points, while boys are not observed with such impacts. Breaking down the heterogeneity further by gender and age groups jointly in Table 11, we find that disaster shocks in early life lower the math-test scores for girls significantly when they just start schools.

It is plausible that disaster experiences have greater impacts at the start of school when children begin their learning process, and there is some catch-up that equalizes achievement outcomes during elementary school as children learn basic skills, but the experiences of prior disaster shocks manifest again as children progress to higher stages of learning and some are able to advance further than others. It has been shown that children in their critical first 1000 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 Table C.8, we estimate heterogeneous effects across countries. We find that children in Pakistan are strongly negatively affected by early life disaster shocks. Children in both Pakistan and Bangladesh are affected by mid-life disaster shocks, although different age groups are affected according to Table C.9. An additional month of mid-life disaster reduces the math-test score by more than 0.05 points in Bangladesh, and an additional month of early life disaster reduces the score by 0.09 points in Pakistan. One important caveat for our results is that we do not capture disaster histories for the same cohort of children over time. Given age-composition-structure differences and disaster-history differences in each country, it could be that the disasters in Bangladesh that matched with mid-life shock timing, given our sample, were more severe and longer lasting, but the Bangladesh sample experienced less severe and lasting early life disasters. Our estimates from Tables 8 and 9 pull the data from different countries together and find overall effects of mid-life and early life disasters as well as current-age-specific effects of disasters under the assumption that effects are homogeneous across countries.

It is also interesting to note that we find positive yet weakly significant estimates of the effects of early life disaster experiences on test scores in our country breakdown for countries other than Pakistan and Bangladesh. As shown in Appendix Figure C.1, while the vast majority of children of appropriate age across all countries took the math exam, there are potentially problematic selection issues in Thailand and Turkmenistan, where students not enrolled have much lower rates of taking the test. Given our prior results on the impact of disasters on enrollments, this could lead to selection bias.

Table C.14, C.15, and C.16 present the heterogeneous effects of disaster exposures on math-test scores using other intensity types across ages or genders, separately or jointly. Overall, there are weak or no effects from recent exposures to natural disasters regardless of the types of disaster intensity, while there are significantly negative effects from early life exposures on math skills if we consider all kinds of disasters or only floods for both boys and girls.

## 6 Conclusions

A 2023 report from UN-ESCAP (2023) indicated that climatic change-induced disasters pose an increasingly serious threat to Asia and the Pacific, which remains the most natural-disaster-prone world region. Disaster resilience has become an important policy concern in educational sectors, where impacts on children from marginalized populations are of particular concern. This paper has focused on estimating disaster effects on children's educational outcomes in seven countries in Asia, with attention to exposures in the first thousand days of life, in middle-childhood and in the period immediately preceding the surveys and tests. Our paper contributes to the existing literature in several ways.

First, as we not only study short-term disaster shocks but also the early life shocks, we contribute to a large literature addressing the immediate and lasting effects of disaster shocks in early life on children's educational outcomes. Second, we explore heterogeneity locally and regionally with a large sample and consider multiple disasters. By using a large sample covering more than 140 thousand children in seven Asian countries and a global record of natural disasters, we are able to estimate multiple disaster shocks effects and our results should be more generalizable than single-country studies.

Our results show, overall, significant negative effects of early life disaster exposures on enrollments and math skills, even in regional fixed effects specifications, 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. Age patterns of enrollments and learning effects of disaster exposures differ across national settings. 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 results are consistent if we only consider floods for natural disaster exposure measure.

In directly using school enrollment and test score data for children, this paper is one of the few studies to establish the lasting effect of having experienced natural disasters in the first 1000 days on schooling enrollments and learning outcomes. Findings highlight the need to more specifically support children affected by disasters 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 |
| between 20 years ago and 10 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 1000 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 1000 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 1000 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 1000 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 1000 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 1000 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 1000 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 1000 days of life 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: The 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 1000 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 1000 days of life 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 1000 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 6: Disasters and enrollments, heterogeneity across age groups

| | (1) | (2) |
|---|---|---|
| **Had disaster in recent 12 mo.** | | |
| $\times$ Age 5–8 | 0.008 | 0.069$^{***}$ |
| | (0.010) | (0.025) |
| $\times$ Age 9–12 | −0.009 | 0.050$^{**}$ |
| | (0.006) | (0.025) |
| $\times$ Age 13–17 | −0.012 | 0.046$^{*}$ |
| | (0.009) | (0.027) |
| **# of mo. with disaster in the first 1000 days** | | |
| $\times$ Age 5–8 | 0.001 | 0.001 |
| | (0.001) | (0.001) |
| $\times$ Age 9–12 | −0.002$^{***}$ | −0.002$^{***}$ |
| | (0.000) | (0.000) |
| $\times$ Age 13–17 | −0.001 | −0.001 |
| | (0.001) | (0.001) |
| Observations | 143645 | 143622 |
| Within country location FE | *Y* | |
| Country $\times$ cluster FE | | *Y* |
| Interview year FE | *Y* | *Y* |
| Interview month FE | *Y* | *Y* |
| Child age FE | *Y* | *Y* |
| Enrollment $t-1$ $\times$ age group FE | *Y* | *Y* |
| Attainment $t$ $\times$ age group FE | *Y* | *Y* |
| Enrollment $t-1$ $\times$ country FE | *Y* | *Y* |
| Attainment $t$ $\times$ country FE | *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 1000 days for children in age 5-8, 9-12, and 13-17 is about 2 months, 3 months, and 4 months, respectively. 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) | (2) |
|---|---|---|
| **Had disaster in recent 12 mo.** | | |
| × Male | | |
| × Age 5–8 | 0.013 | 0.072*** |
| | (0.009) | (0.025) |
| × Age 9–12 | −0.010 | 0.049* |
| | (0.007) | (0.025) |
| × Age 13–17 | −0.017 | 0.041 |
| | (0.010) | (0.027) |
| × Female | | |
| × Age 5–8 | 0.003 | 0.064** |
| | (0.010) | (0.025) |
| × Age 9–12 | −0.009 | 0.051** |
| | (0.006) | (0.025) |
| × Age 13–17 | −0.008 | 0.051* |
| | (0.009) | (0.027) |
| **# of mo. with disaster in the first 1000 days** | | |
| × Male | | |
| × Age 5–8 | 0.001 | 0.001 |
| | (0.001) | (0.001) |
| × Age 9–12 | −0.003*** | −0.003*** |
| | (0.001) | (0.001) |
| × Age 13–17 | −0.001 | −0.001 |
| | (0.001) | (0.001) |
| × Female | | |
| × Age 5–8 | 0.001 | 0.001 |
| | (0.001) | (0.001) |
| × Age 9–12 | −0.000 | −0.000 |
| | (0.000) | (0.000) |
| × Age 13–17 | −0.001 | −0.001 |
| | (0.001) | (0.001) |
| Observations | 143645 | 143622 |
| Within country location FE | *Y* | |
| Country × cluster FE | | *Y* |
| Interview year FE | *Y* | *Y* |
| Interview month FE | *Y* | *Y* |
| Child age FE | *Y* | *Y* |
| Enrollment $t-1$ × age group FE | *Y* | *Y* |
| Attainment $t$ × age group FE | *Y* | *Y* |
| Enrollment $t-1$ × country FE | *Y* | *Y* |
| Attainment $t$ × country FE | *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 1000 days of life 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 groups (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 1000 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. Standard errors, clustered at the within country location level, are reported in parentheses.

Table 8: The effects of disaster shocks on math test scores

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Recent** experience: had disaster* | | | | |
| in recent 12 mo. | $-0.122$ | 0.167 | $-0.070$ | 0.279 |
| | (0.190) | (0.618) | (0.171) | (0.594) |
| in yr prior 12 mo. ago | 0.066 | $-0.355$ | $-0.014$ | $-0.390$ |
| | (0.181) | (0.532) | (0.165) | (0.527) |
| ***Mid-child life** experience: # of mo. with disaster* | | | | |
| (> 1000 days) & (< yr. before last yr.) | $-0.035^{**}$ | $-0.027$ | $-0.024$ | $-0.023$ |
| | (0.017) | (0.017) | (0.016) | (0.017) |
| ***Early-life** experience: # of mo. with disaster* | | | | |
| in the first 1000 days | $-0.040^{***}$ | $-0.034^{**}$ | $-0.031^{**}$ | $-0.029^{**}$ |
| | (0.015) | (0.015) | (0.015) | (0.014) |
| Female | | | $-0.420^{***}$ | $-0.411^{***}$ |
| | | | (0.061) | (0.064) |
| Mother is alive | | | $0.324^{**}$ | 0.239 |
| | | | (0.160) | (0.159) |
| Father is alive | | | $0.227^{**}$ | 0.172 |
| | | | (0.105) | (0.112) |
| Mother is alive × living in same HH | | | 0.057 | $0.157^{*}$ |
| | | | (0.080) | (0.090) |
| Father is alive × living in same HH | | | $-0.217^{***}$ | $-0.214^{***}$ |
| | | | (0.061) | (0.063) |
| Mother ever educated | | | $1.340^{***}$ | $0.974^{***}$ |
| | | | (0.082) | (0.077) |
| Mother ever educated × has secondary education | | | $0.996^{***}$ | $0.821^{***}$ |
| | | | (0.067) | (0.064) |
| Observations | 78657 | 78502 | 78305 | 78141 |
| Within country location FE | *Y* | | *Y* | |
| Country × cluster FE | | *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 1000 days of life 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 1000 days of life 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 1000 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 8. Standard errors, clustered at the within country location level, are reported in parentheses.

Table 9: Disasters and math-test scores, heterogeneity across ages groups

| | (1) | (2) |
|---|---|---|
| **# of mo. with disaster in mid-child life** | | |
| × Age 7–9 | −0.020 | −0.007 |
| | (0.025) | (0.026) |
| × Age 10–12 | −0.015 | −0.005 |
| | (0.023) | (0.023) |
| × Age 13–14 | −0.017 | −0.007 |
| | (0.022) | (0.022) |
| **# of mo. with disaster in the first 1000 days** | | |
| × Age 7–9 | −0.038* | −0.022 |
| | (0.022) | (0.021) |
| × Age 10–12 | 0.014 | 0.008 |
| | (0.017) | (0.017) |
| × Age 13–14 | −0.030 | −0.027 |
| | (0.022) | (0.023) |
| Observations | 78303 | 78139 |
| Within country location FE | *Y* | |
| Country × cluster FE | | *Y* |
| Interview year FE | *Y* | *Y* |
| Interview month FE | *Y* | *Y* |
| Child age FE | *Y* | *Y* |
| Attainment $t$ × country FE | *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 1000 days of life 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 1000 days of life 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 groups, about 56% of them have experienced natural disaster in most recent 12 months. The average number of months with disaster in first 1000 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 8. Standard errors, clustered at the within country location level, are reported in parentheses.

Table 10: Disasters and math-test scores, heterogeneity between genders

| | (1) | (2) |
|---|---|---|
| **# of mo. with disaster in mid-child life** | | |
| × Male | $-0.036^{**}$ | $-0.035^{**}$ |
| | (0.016) | (0.017) |
| × Female | $-0.014$ | $-0.013$ |
| | (0.017) | (0.017) |
| **# of mo. with disaster in the first 1000 days** | | |
| × Male | $-0.028$ | $-0.029^{*}$ |
| | (0.017) | (0.017) |
| × Female | $-0.034^{**}$ | $-0.030^{**}$ |
| | (0.015) | (0.015) |
| Observations | 78305 | 78141 |
| Within country location FE | *Y* | |
| Country × cluster FE | | *Y* |
| Interview year FE | *Y* | *Y* |
| Interview month FE | *Y* | *Y* |
| Child age FE | *Y* | *Y* |
| Attainment $t$ × country FE | *Y* | *Y* |

*Note:* This table shows heterogeneity analysis between genders of disaster effects on math-test scores. This corresponds to Equation 3 with interactions between disaster shocks and gender.
The mid-child life is defined as the period between the first 1000 days of life 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, about 56% have experienced natural disaster in most recent 12 months. The average number of months with disaster in first 1000 days for both boys and girls is about 3 months. The average number of months with disaster in mid-child life is about 7.7 months for children of both genders. The average math test score for girls is 14.4 with standard deviation 7.3. The average math test score for boys is 14 and standard deviation is 7.6. The distribution of math test score across ages and countries is shown in Figure 8. Standard errors, clustered at the within country location level, are reported in parentheses.

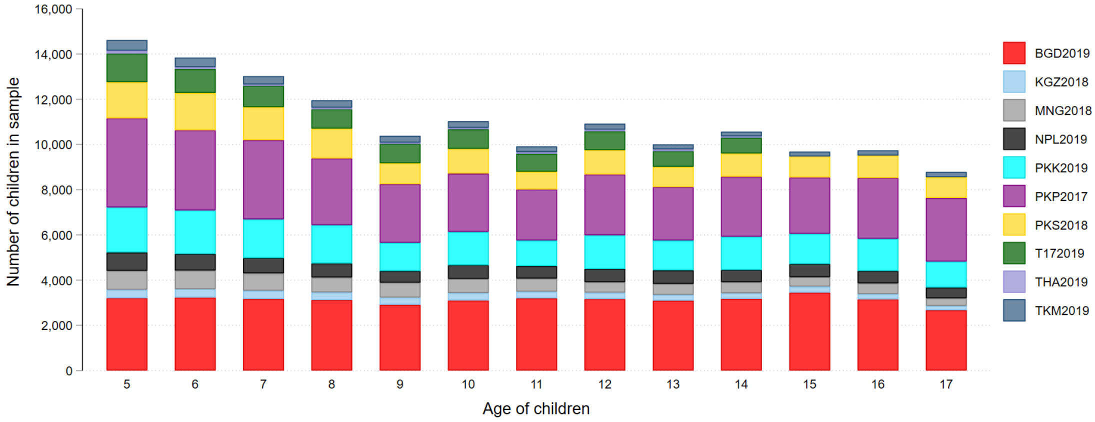
Table 11: Disasters and math-test scores, heterogeneity across gender and ages groups

| | (1) | (2) |
|---|---|---|
| **# of mo. with disaster in mid-child life** | | |
| × Male | | |
| × Age 7–9 | −0.037 | −0.024 |
| | (0.024) | (0.025) |
| × Age 10–12 | −0.023 | −0.013 |
| | (0.023) | (0.023) |
| × Age 13–14 | −0.026 | −0.015 |
| | (0.022) | (0.022) |
| × Female | | |
| × Age 7–9 | −0.004 | 0.009 |
| | (0.026) | (0.027) |
| × Age 10–12 | −0.006 | 0.003 |
| | (0.023) | (0.023) |
| × Age 13–14 | −0.007 | 0.001 |
| | (0.022) | (0.022) |
| **# of mo. with disaster in the first 1000 days** | | |
| × Male | | |
| × Age 7–9 | −0.036 | −0.022 |
| | (0.027) | (0.026) |
| × Age 10–12 | 0.015 | 0.013 |
| | (0.021) | (0.020) |
| × Age 13–14 | −0.018 | −0.020 |
| | (0.031) | (0.033) |
| × Female | | |
| × Age 7–9 | −0.041** | −0.022 |
| | (0.021) | (0.019) |
| × Age 10–12 | 0.012 | 0.001 |
| | (0.019) | (0.019) |
| × Age 13–14 | −0.041* | −0.034 |
| | (0.024) | (0.024) |
| Observations | 78303 | 78139 |
| Within country location FE | *Y* | |
| Country × cluster FE | | *Y* |
| Interview year FE | *Y* | *Y* |
| Interview month FE | *Y* | *Y* |
| Child age FE | *Y* | *Y* |
| Attainment $t$ × country FE | *Y* | *Y* |

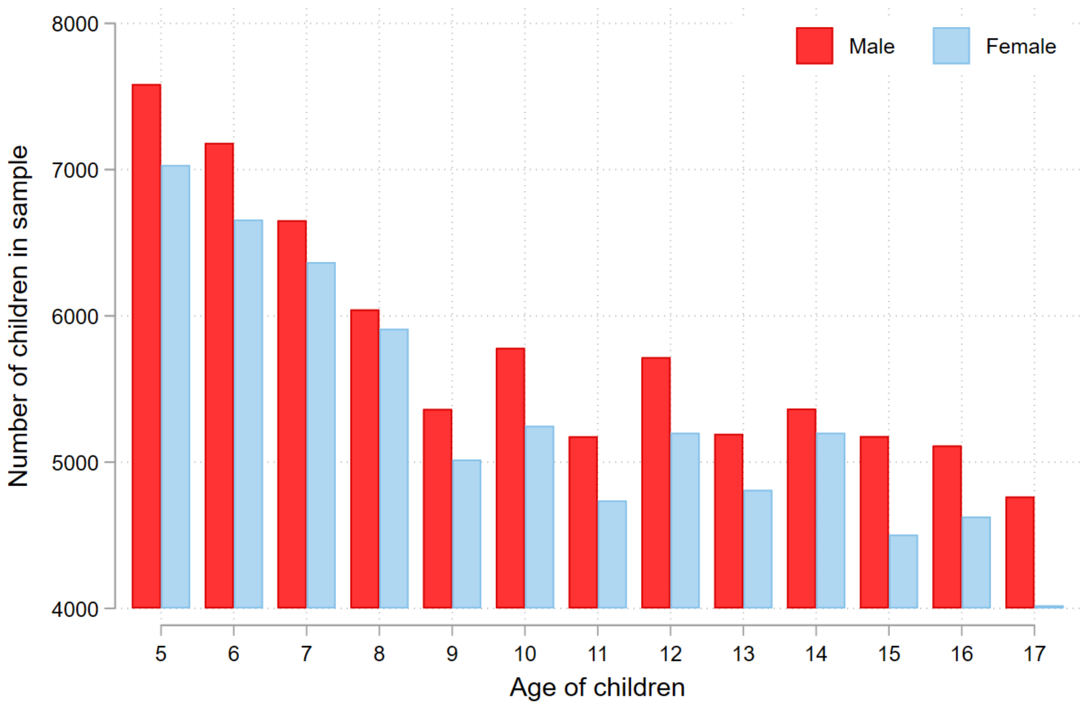
*Note:* This table shows heterogeneity analyses across gender and ages of disaster effects on math-test scores. This corresponds to Equation 3 with interacting disaster shocks between age groups and gender. The first 1000 days of life is defined as the period from conception to 24 months of age in child development, hence in total, there are 33 months in the period. The mid-child life is defined as the period between the first 1000 days of life 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 groups, about 56% have experienced natural disaster in most recent 12 months. The average number of months with disaster in first 1000 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 8. 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



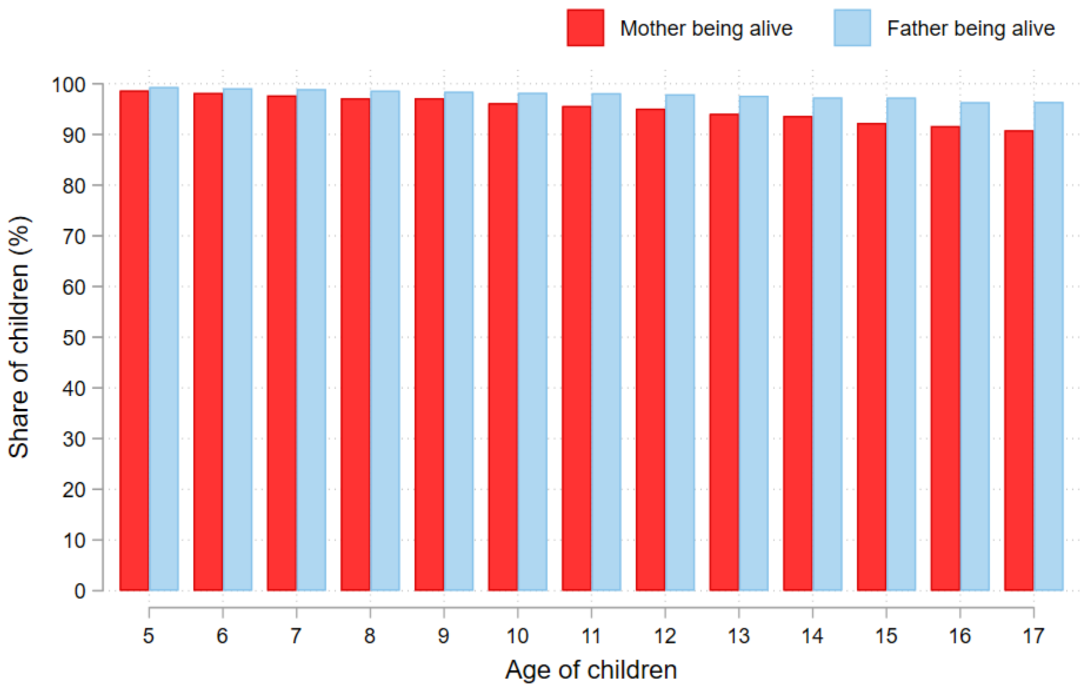

(b) Sample Size Across Gender and Ages



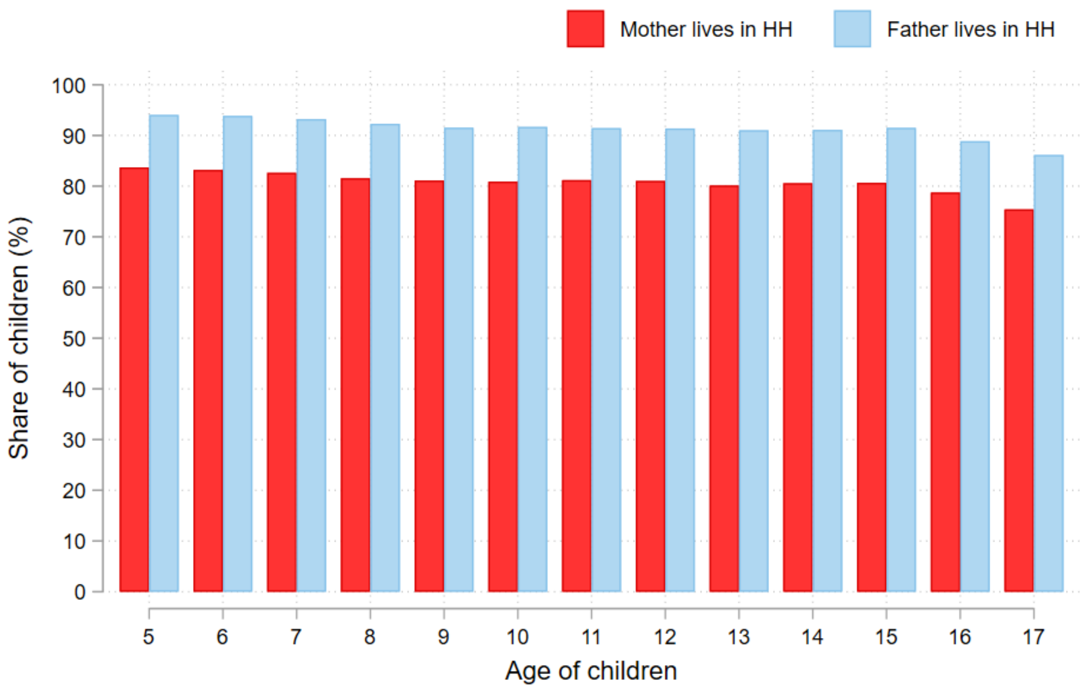

*Note:* Panel (a) shows number of children in each age and country. There are 144,471 children in full sample dominated by Bangladesh and Pakistan. For every age and country, there are more boys interviewed than girls. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan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

Figure 2: Parental Presence by Children's Ages

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



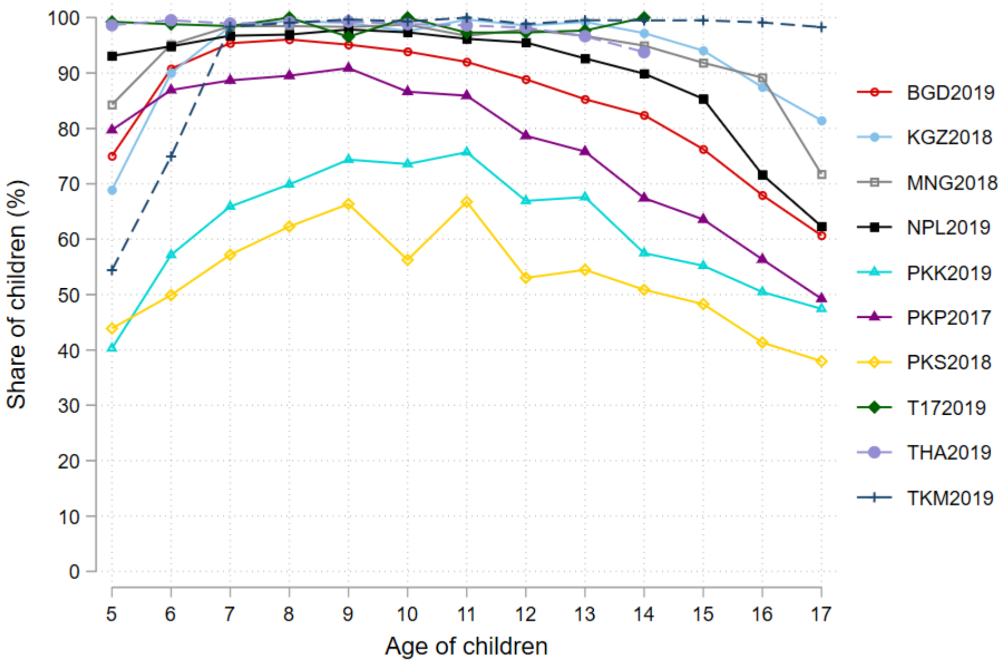

(b) Share of Parents Living with Mother or Father by Ages



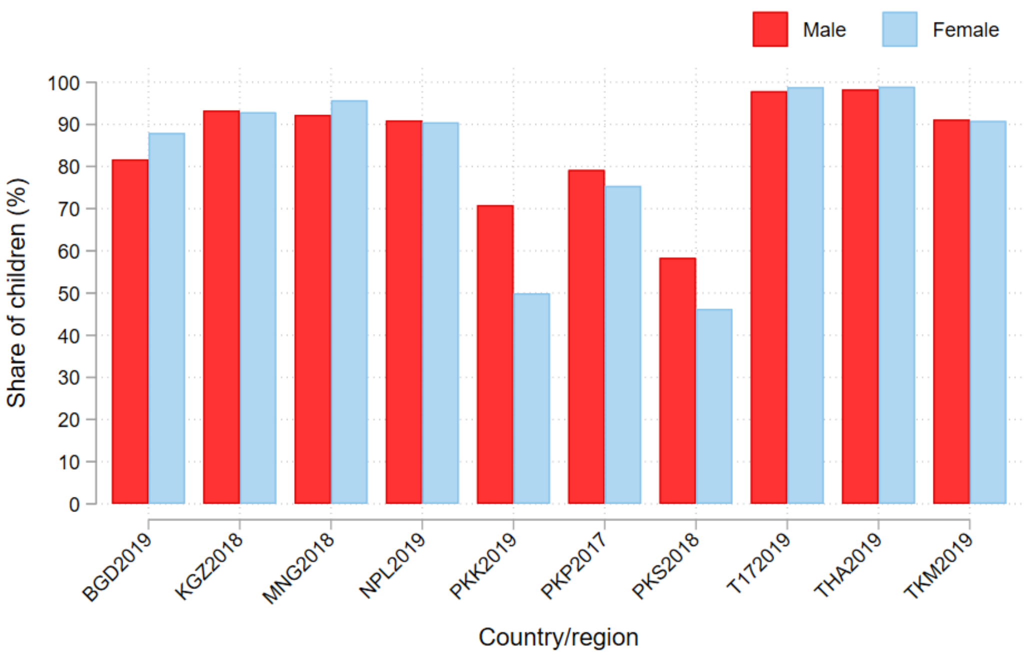

*Note:* Panel (a) shows the share of children with mother or father who is alive by child ages. Panel (b) shows the share of children living with either mother or father by ages. Blue (orange) bars represent shares of fathers (mothers).

Figure 3: Enrollment Fraction in Survey Year

(a) Enrollment Fraction in Survey Year by Ages and Countries



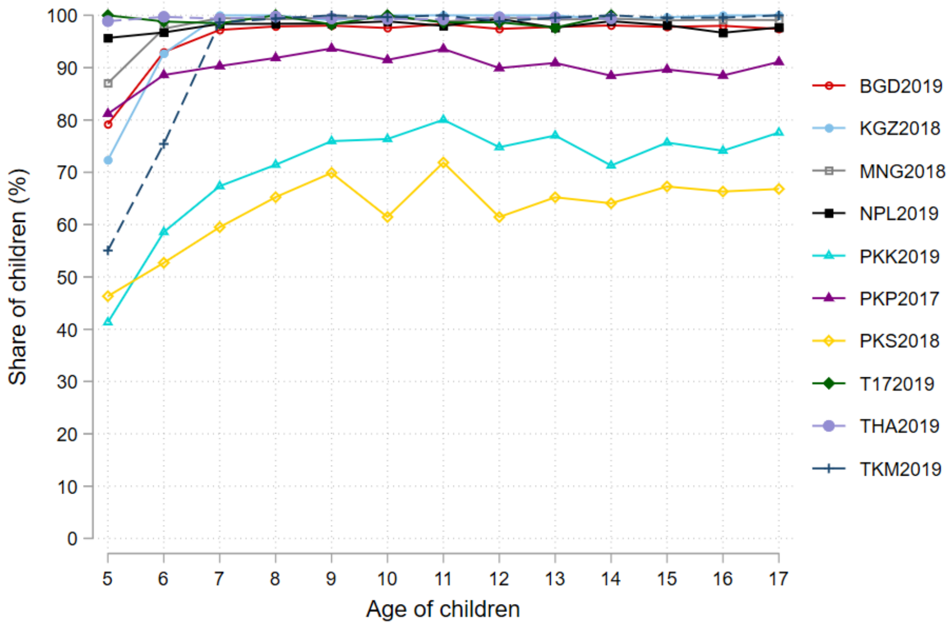

(b) Enrollment Fraction in Survey by Gender and Country



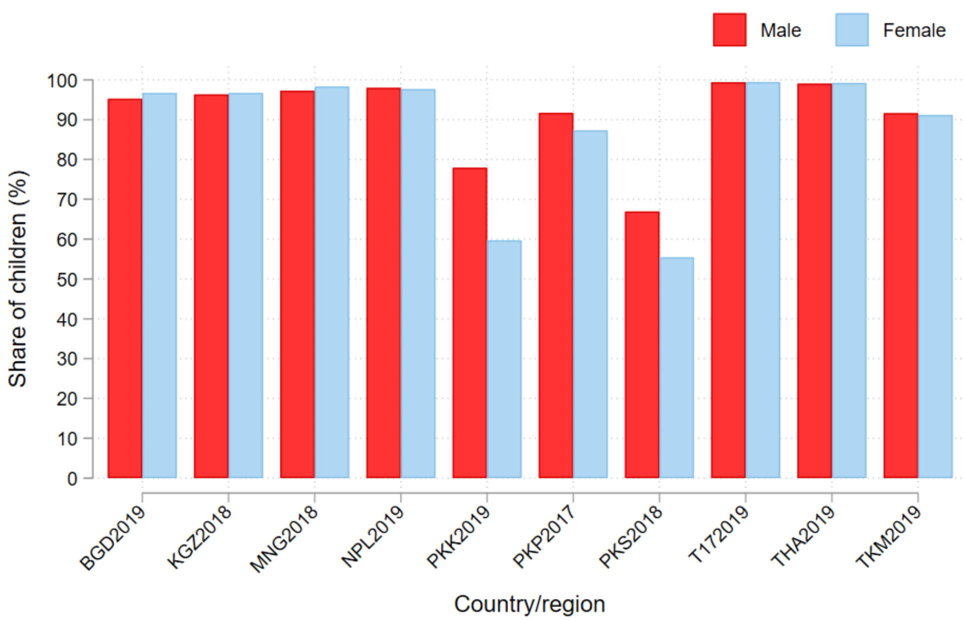

*Note:* Enrollment fraction in survey year. In Thailand, data are observed only up to age 14, in all other countries, data are available up to age 17. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS**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

Figure 4: Share of Children Ever-enrolled

(a) Share of Children Ever Enrolled in School by Ages and Countries



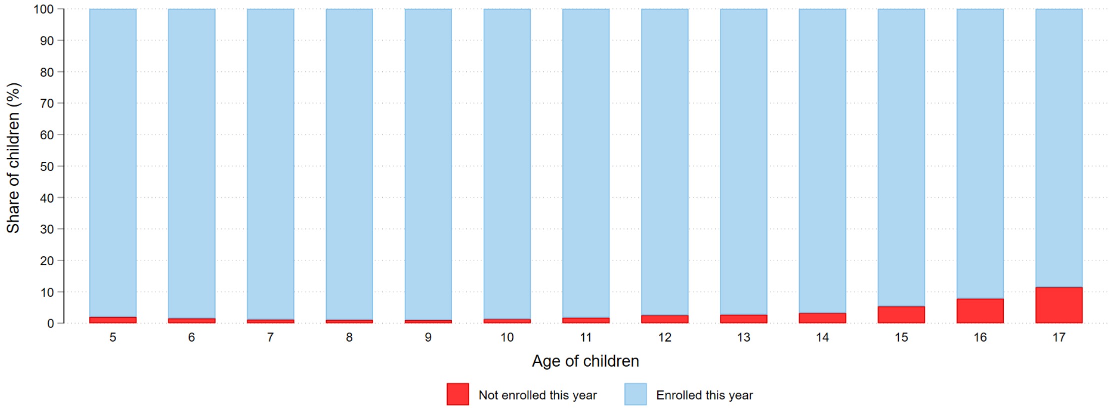

(b) Share of Children Ever Enrolled in School by Gender and Countries



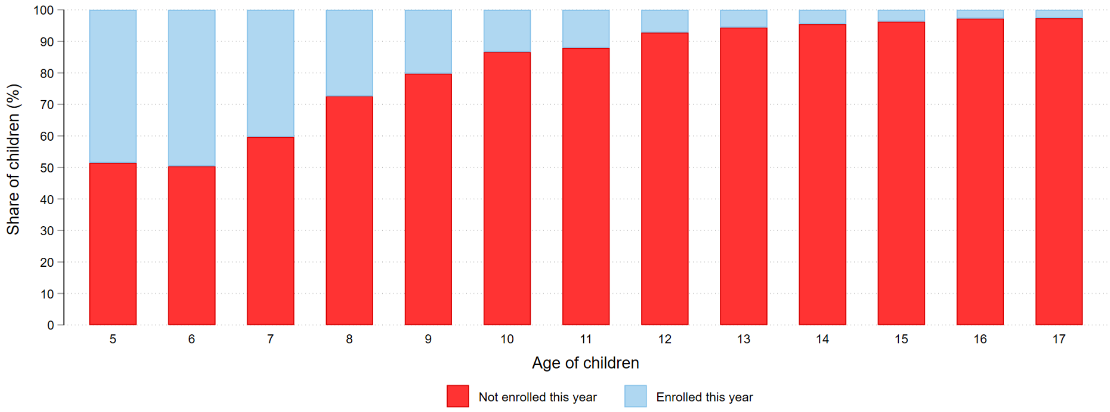

*Note:* The survey asks if a child has ever been enrolled in school. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged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

Figure 5: Enrollment Transition Probabilities By Ages

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



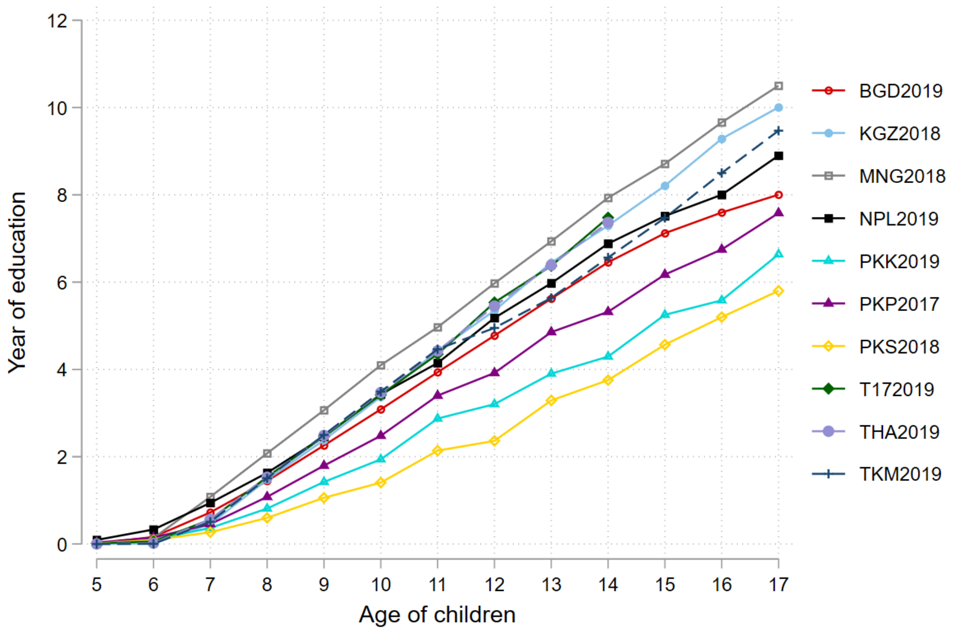

(b) Enrollment Fraction in Survey Year Conditional on Being **Enrolled** Previous Year



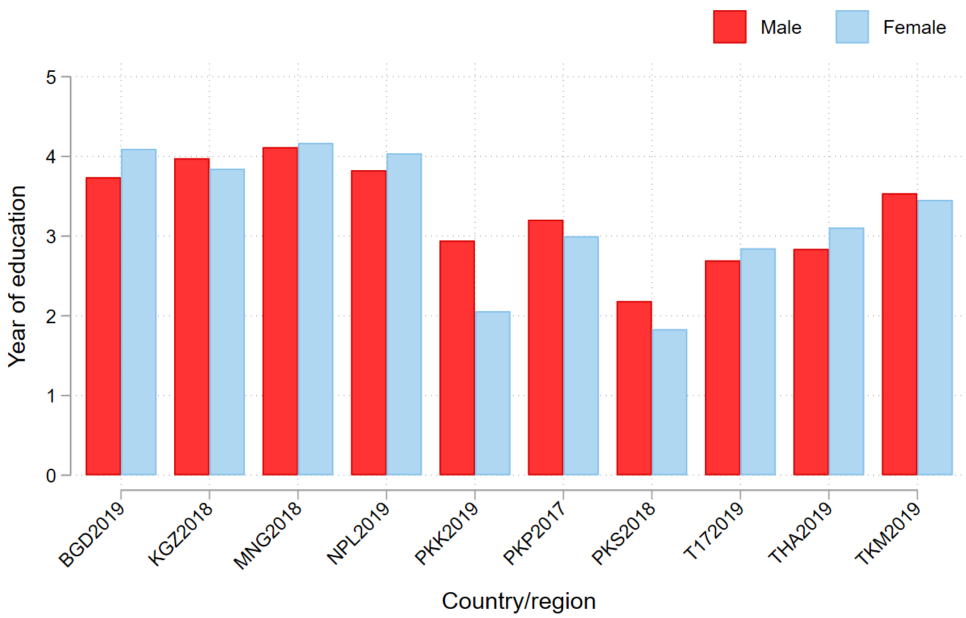

*Note:* Enrollment fraction in survey year conditional on being **Enrolled** previous year. The results show conditional probabilities.

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

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



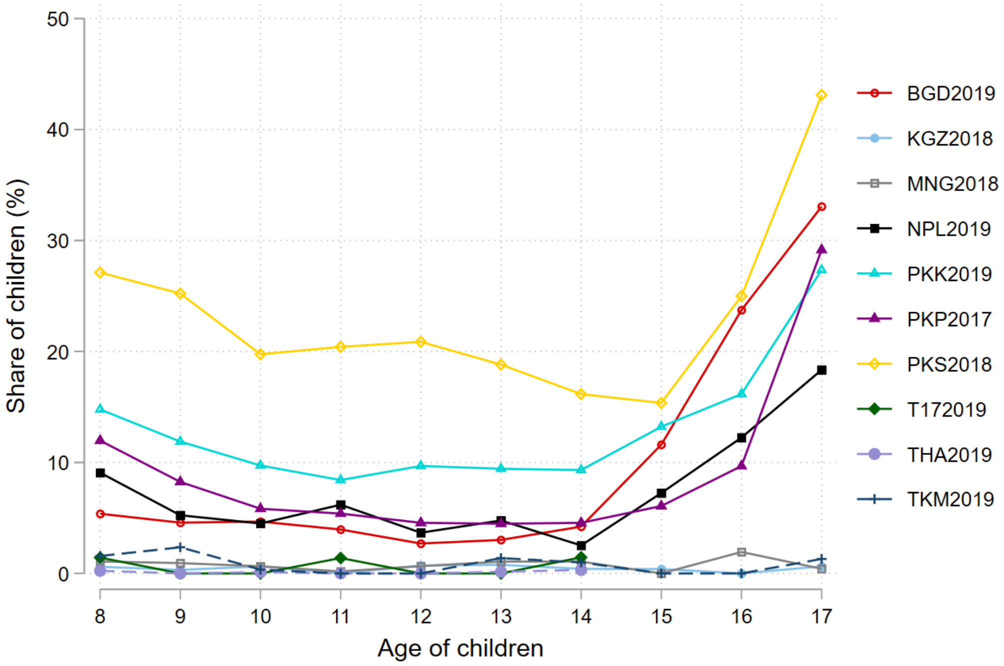

(b) Average Grades of Schooling Completed by Gender and Countries (All Available Ages)



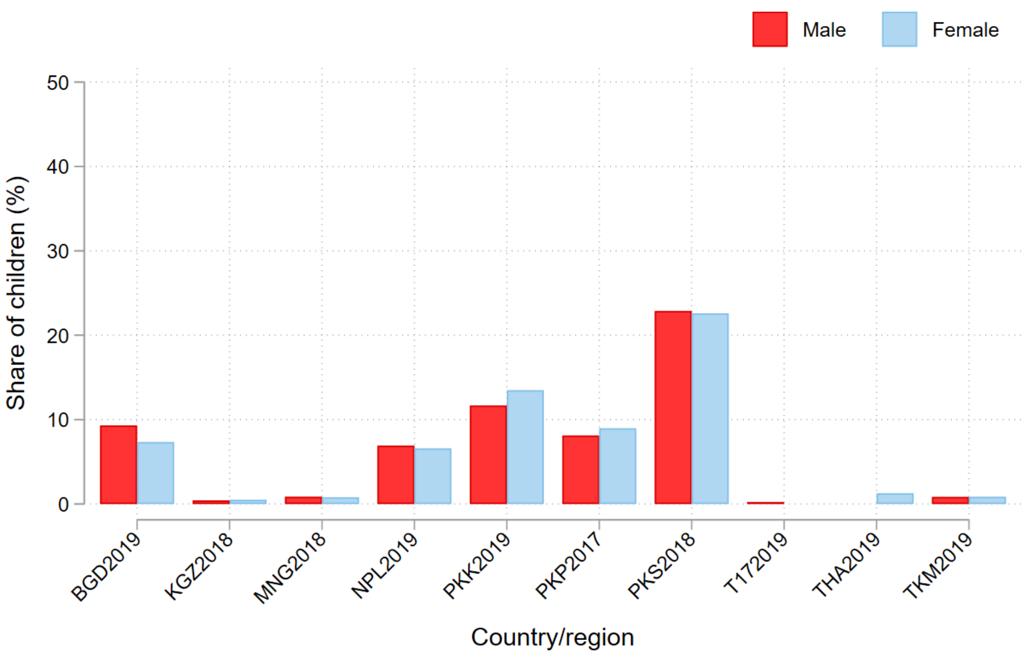

*Note:* In Thailand, data are observed only up to age 14, in all other countries, data are available up to age 17. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **KGZ**).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: Retention (Grade Repetition) By Age and Country

(a) Retention Rate by Ages and Countries



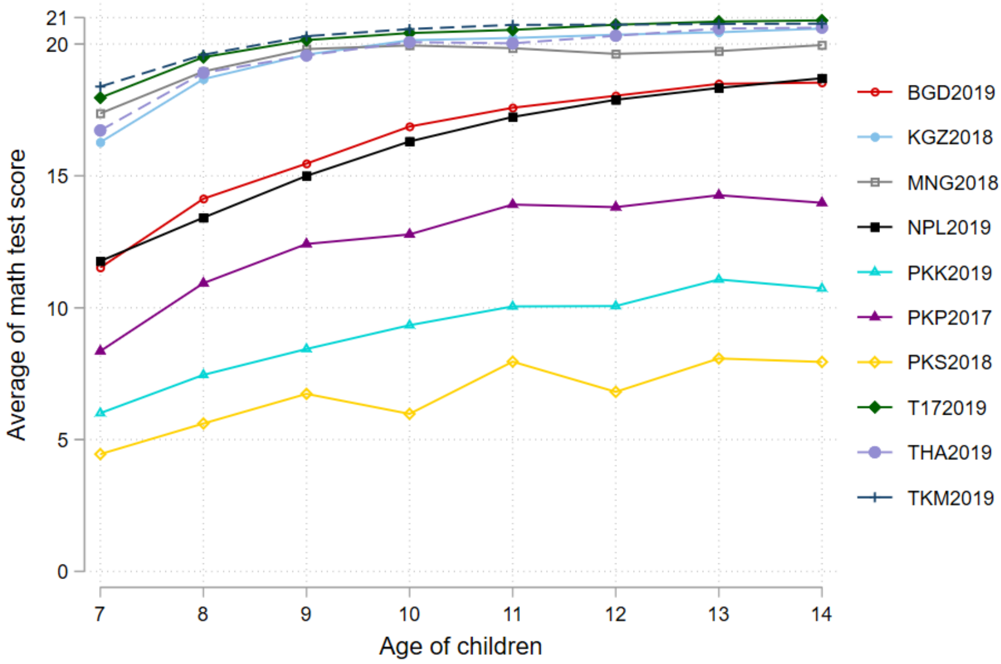

(b) Retention Rate by Gender and Countries (≥ Age 8)



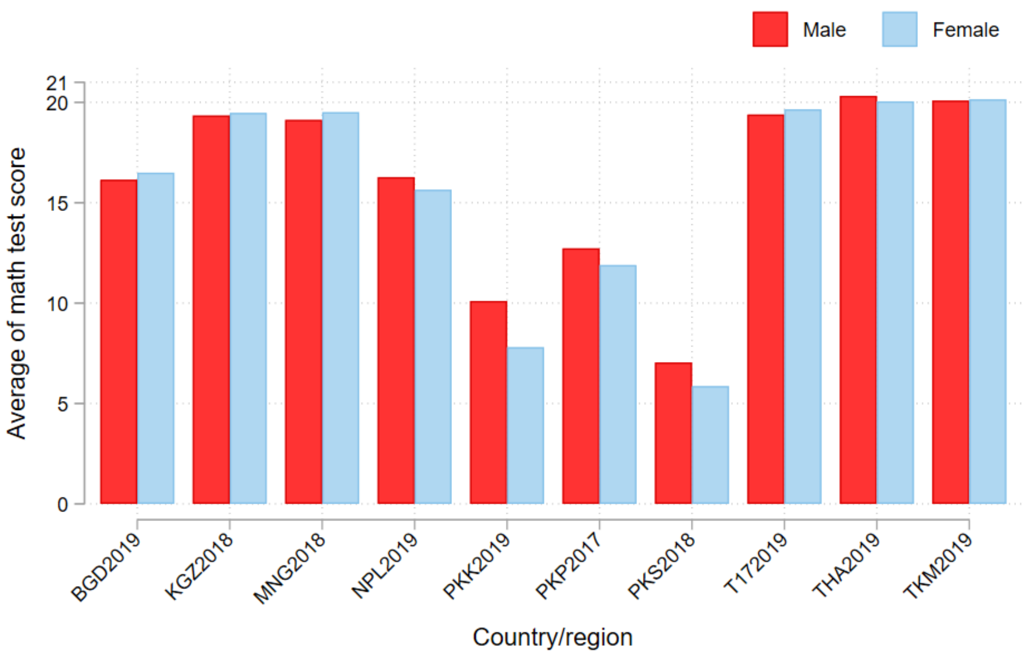

*Note:* If a child reports attending the same grade this and last year, a child is repeating a grade and experiencing grade retention. Gender indicator is 0 for male and 1 for female. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **KGZ**).

Figure 8: Distribution of Math-Test Scores

(a) Average of Math-Test Scores by Ages and Countries

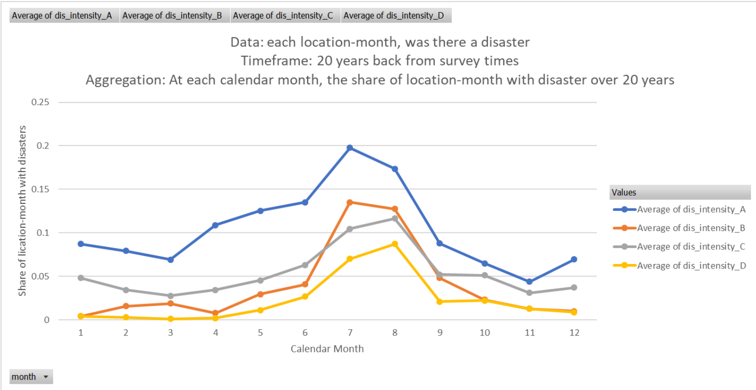



(b) Average of Math-Test Scores by Gender and Countries (Age 7-14)

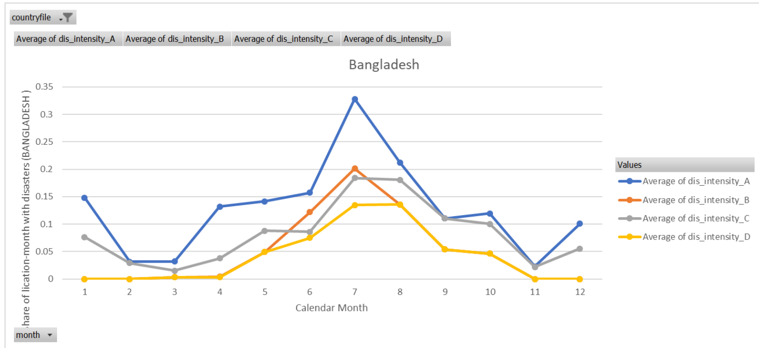



*Note:* Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** Bangkok only)), and Kyrgyzstan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

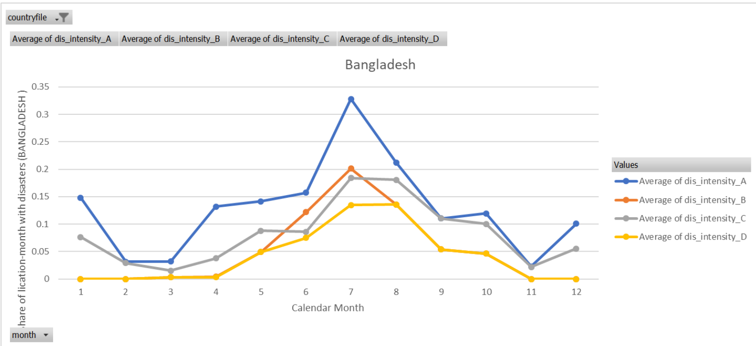
Figure 9: Share of Location-month that Experience Disaster Shock in Each Calendar Month over 20 Years



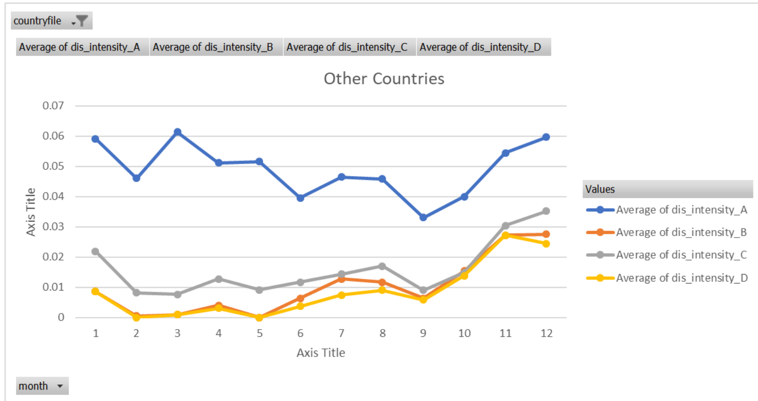

(a) All Countries




(b) Bangladesh Only




(c) Pakistan Only




(d) Other Countries

*Note:* For each location in every month from latest survey month to 20 years prio to the survey, we construct a disaster indicator with the 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.

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ONLINE APPENDIX

# Are Natural Disasters Disastrous for Learning? 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) (MICS6) 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 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 a randomly selected child aged 5 to 17, and this new questionnaire includes interviewer-administered tests to assess child cognitive skills directly. In total, six model 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. The current study uses information from the household, individual, and children aged 5 to 17 questionnaires.

Among Asian countries covered by MICS6, we focus on low- and middle-income countries whose data is collected before the COVID-19 pandemic. Our analysis includes countries from South Asia (Bangladesh (2019), Nepal (2019), Pakistan (2017-2019)), East Asia and the Pacific (Mongolia (2018), Thailand (2019)), and Central Asia (Kyrgyzstan (2018), Turkmenistan (2019)).[A.1]

A.1. We do not include countries whose survey time frame overlapped with the COVID-19 pandemic. For example, MICS6's Vietnam survey, which was fielded between 2020 and 2021, is excluded from our analysis.

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 (Stocker 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).

Table 1 provides country-specific data collection time window and sample size information for the subset of MICS6 countries we use in this study.

### A.2 Measures: Education and Skills

In this paper, we use MICS6 data on school enrollment, attainment, and grade progression for children aged 5 to 17 as well as MICS6 data on foundational learning skills for children aged 7 to 14. We explain in this section the construction of the human capital outcome variables used in this paper.

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 selected child is between 7 and 14 years of age. The assessment 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 includes a categorical value for the "level" of school and a numerical value for the "grade" within that level of school. Since education systems differ across countries, we construct a comparable enrolled "year of education" (yoe) variable based on "level" and "grade" jointly. Let *edu_yoe_highest*, *edu_yoe_lasty*, and *edu_yoe_thisy* denote the constructed year 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. $n = 1$: $edu\_everschool = 0$, $edu\_enrollasty = \text{NA}$, $edu\_enrolthisy = 0$.
6. $n = 1$: $edu\_everschool = 0$, $edu\_enrollasty = 0$, $edu\_enrolthisy = \text{NA}$.
7. $n = 9$: $edu\_everschool = \text{NA}$, $edu\_enrollasty = 1$, $edu\_enrolthisy = 1$.
8. $n = 0$: $edu\_everschool = \text{NA}$, $edu\_enrollasty = 1$, and $edu\_enrolthisy = 0$.
9. $n = 2$: $edu\_everschool = \text{NA}$, $edu\_enrollasty = 0$, and $edu\_enrolthisy = 1$.
10. $n = 1$: $edu\_everschool = \text{NA}$, $edu\_enrollasty = 0$, and $edu\_enrolthisy = 0$.

Note that in case 4 above, while the response logic is correct, 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.

**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. $A_{max}$ 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.

In the enumeration above, 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 path 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 path D and E have $A_{t-1} = A_{max}$.

In the enumeration above, 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 path D and E have $A_{t-1} = A_{max}$.

### A.2.4 MICS6 Test Scores

We use foundational learning skills module in MICS6 children 5-17 questionnaire to construct the test score for reading and math. Only children between age 7-14 are tested after the permission is given by respondent, the child is ready to get started.

For reading test, there are several components including (1) reading words in a story correctly (2) how well the story is read by the child (3) comprehension of the story. Due to language difference, the reading test taken by each child is not exactly the same. The story is provided in English, Spanish, or French and if the child does not know one of those languages or does not want to try, then the reading test is skipped.

For component (1), raw variable *FL20B* records the number of words missed or incorrect, hence we are able to construct *variable read_score_wordcorrect* by counting the number of correct words read. Note that for each country, the story varies though not too much. For Mongolia, 67 words are recorded. So it is *variable read_score_wordcorrect* = 67-FL20B. Story in Turkmenistan has 69 words. All other country and files have 72 words in the story. Component (2) is measured by these questions: at least one word is correct, did not read any word correctly, and did not try to read story. We do not use this component as it repeats information captured in component (1) showing more straightforward result for vocabulary and reading ability. Component (3) includes five questions asked to test how well children understand the story, and each one is counted for one score. Variable *read_score_comp* is generated by adding all scores gained from each question. We give this 1 score if it is answered correctly, 0 if incorrect or not attempt. At last, we sum up *variable read_score_wordcorrect* and *read_score_comp* to obtain the total reading score, *read_score_total*.

Math test is uniform across countries and the components include (1) 6 questions to recognize symbol 9, 12, 30, 48, 74, and 731 (2) 5 questions to identify bigger of two number (between 7 and 5, or 65 and 67, for example) (3) 5 questions to add two numbers (4) 5 questions to identify next number (for example, given 20, X, 40, and 50, which number should X be).

For each questions, most of countries record only if each question is answered correctly or not. We construct score 1 if it is correct, 0 if incorrect or no attempt. The missing value stays as missing. *math_score_total* = *math_score_sym* + *math_score_big* + *math_score_add* + *math_score_next*. One thing that may be interesting is that in Kyrgyzstan, more details are offered on how the question is answered. They record all answers for the questions except for "recognize symbol". For example, to compare 5 and 7, they record as string if the child chooses 5 or 7 or not attempt. As for "add number" such as 3+2, they record all wrong answers from children like 2, 3, 10, 51, 55. In Pakistan, they use the same strategy as Kyrgyzstan, but in different variables. So, they record all wrong answers, but also just provide "correct or not" variables. We do not include the wrong answers to construct the test score as cognitive skills measure as it is not available for all countries in this paper. Hence we have uniform variable *math_score_total*.

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

#### A.3.1 Child Characteristics

As the MICS survey is implemented at household level and record individuals in the household with a focus on women and children, if the child selected in one household for children 5-17 questionnaire is the respondent for household questionnaire, then some basic information is recorded in household individual raw data (named as "hl", while the children 5-17 raw data file is named "fs"). This is also the case for educational outcome except test score as mentioned in previous sections.

Birth date comes from CB2 and HL5 from "fs" file and "hl" file, respectively, prioritizing value from CB2. Children age is obtained from CB3 from "fs" data file and HL6 from "hl" file if CB3 is missing. Gender is recorded for everyone in our sample simply from "fs" file and HL4 is the raw variable.

### 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 every observation in children age 5-19 module which is corresponded with "fs" file with the people in household individuals module which is essentially "hl" file. Then using HL5, we are able to obtain mother and father birth year and month while HL6 is used to confirm their age.

The education information of parents exists in both "fs" and "hl" files. The children 5-17 questionnaire does not have question particularly ask for this yet there is variable "melevel" labeled as "mother education" in "fs" file. In "hl" file, there are "melevel" and "felevel" variables denoting mother education and father education respectively. Another way to obtain parents education is the same as how we construct the age variables, by linking mother and father individuals. After comparing sample size for each case, we decide to use "melevel" from "fs" file and replace that from "hl" file if it is missing, and directly use "felevel" from "hl" file for father education.

### A.3.3 Parental Loss and Cohabitation

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 parental-child co-residence status. Figure 2 present distributions of parental loss and parental-child co-residence status across .

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

## B.1 The EM-DAT Dataset

We use EM-DAT (1900-2023) to construct natural disaster variables. EM-DAT is an international database compiled by the Centre for Research on the Epidemiology of Disaster (CRED) and contains comprehensive information on disasters that have resulted in significant loss of human life. It records the occurrence and impacts of over 21,000 disasters worldwide from 1900 to the present. EM-DAT has been used for decision-making for disaster preparedness, vulnerability assessment, and prioritizing resources for disaster response.

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 (Mavhura and Aryal 2023; Guha-Sapir, Below, and Hoyois). Our study exclusively considers events classified as natural disasters in EM-DAT. The dataset is compiled from various sources including UN agencies, non-governmental organisations, insurance companies, research institutes, and press agencies. A disaster is included in EM-DAT if it meets at least one of the following criteria: (a) 10 or more people are killed in the disaster, (b) 100 or more people are affected by the disaster, (c) a state of emergency is declared due to the disaster, or (d) international assistance is called for in response to the disaster (Panwar and Sen 2020; Mavhura and Aryal 2023; Sy et al. 2019).

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 provides the administrative-level code and location names for all 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. Additionally, some EM-DAT entries include economic impact information as measured by total estimated damages, reconstruction cost and insured losses associated with each disaster.

We jointly use the number of death and the number of individuals impacted by disasters to classify the severity of disasters and consider the effects of all disasters as well as more severe disasters in our analysis. 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 "Location" variable names across location names across administrative levels.

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

## C Additional Figures and Tables (Online)

This section provides additional tables and figures. We present additional summary statistics for children and parental characteristics in Table C.1 and Table C.2. Table C.3 presents migratory history summary statistics for the mothers of children. Figure C.1 and Figure C.2 present share of observations reporting math and reading test scores, respectively. Figure C.3, Figure C.4 and Figure C.5 plot parental and household characteristics. Distribution of progression and reading test scores are presented in Figure C.6 and Figure C.7, respectively.

Supplementary analyses results are shown in the other tables. Table C.4 shows results for effects of natural disasters on enrollment with various disaster exposure measures. Table C.5 and Table C.6 present additional results for heterogeneous analysis for natural disaster exposure and enrollments. For math test score outcome, Table C.7 shows results using different measures for disaster shock, while Table C.8 and Table C.9 show additional results for heterogeneous effects.

Table C.10, Table C.11, and Table C.12 present effects on enrollment outcome using other types of natural disaster exposure measure. Additionally, math test scores effects of exposure to other types of natural disasters are presented in Table C.13, Table C.14, Table C.15, and Table C.16.

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. The average mothers and fathers about around 36 and 44 years old, respectively.

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 including parents' education status and cohabitation.

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. "Residential duration exceeds age" is a binary variable being 1 if mother has been living in the current location since the conception of the child. "Ratio of residential duration to age" denotes the share of years of the child having lived in the same location to her lifespan. Imagine one child is 10 years old, and she has been living in the current location for 7 years, then this is calculated as 7/10.

Table C.4: Regression of enrollment t on disaster using different recent shock 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 1000 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 $\times$ living in same HH | $0.025^{***}$ | $0.025^{***}$ | $0.025^{***}$ | $0.025^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Father is alive $\times$ 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 $\times$ 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 $t-1$ $\times$ age group FE | $Y$ | $Y$ | $Y$ | $Y$ |
| Attainment $t$ $\times$ age group FE | $Y$ | $Y$ | $Y$ | $Y$ |
| Enrollment $t-1$ $\times$ country FE | $Y$ | $Y$ | $Y$ | $Y$ |
| Attainment $t$ $\times$ country FE | $Y$ | $Y$ | $Y$ | $Y$ |

*Note:* This table shows regression result of Equation 2 using different measure for recent shock. 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.5: Disaster and enrollment, heterogeneity across ages groups and countries

| | (1) | (2) |
|---|---|---|
| **Had disaster in recent 12 mo.** | | |
| × Pakistan | | |
| × Age 5–8 | −0.105* | 0.040 |
| | (0.056) | (0.084) |
| × Age 9–12 | −0.110** | 0.034 |
| | (0.055) | (0.084) |
| × Age 13–17 | −0.101* | 0.044 |
| | (0.058) | (0.086) |
| × Bangladesh | | |
| × Age 5–8 | 0.044*** | 0.297*** |
| | (0.014) | (0.106) |
| × Age 9–12 | −0.011 | 0.240** |
| | (0.008) | (0.109) |
| × Age 13–17 | −0.027** | 0.223** |
| | (0.012) | (0.111) |
| × Other countries | | |
| × Age 5–8 | −0.005 | 0.039* |
| | (0.008) | (0.020) |
| × Age 9–12 | −0.013* | 0.031 |
| | (0.007) | (0.020) |
| × Age 13–17 | −0.013 | 0.033 |
| | (0.010) | (0.022) |
| **# of mo. with disaster in the first 1000 days** | | |
| × Pakistan | | |
| × Age 5–8 | −0.006** | −0.006** |
| | (0.003) | (0.003) |
| × Age 9–12 | −0.001 | −0.001 |
| | (0.001) | (0.001) |
| × Age 13–17 | −0.001 | −0.001 |
| | (0.002) | (0.002) |
| × Bangladesh | | |
| × Age 5–8 | 0.003 | 0.003 |
| | (0.002) | (0.002) |
| × Age 9–12 | −0.002** | −0.002* |
| | (0.001) | (0.001) |
| × Age 13–17 | −0.003*** | −0.003*** |
| | (0.001) | (0.001) |
| × Other countries | | |
| × Age 5–8 | 0.002*** | 0.002*** |
| | (0.000) | (0.000) |
| × Age 9–12 | −0.000 | −0.000 |
| | (0.000) | (0.000) |
| × Age 13–17 | −0.001 | −0.001 |
| | (0.001) | (0.001) |
| Observations | 143645 | 143622 |
| Within country location FE | $Y$ | |
| Country × cluster FE | | $Y$ |
| Interview year FE | $Y$ | $Y$ |
| Interview month FE | $Y$ | $Y$ |
| Child age FE | $Y$ | $Y$ |
| Enrollment $t-1$ × age group FE | $Y$ | $Y$ |
| Attainment $t$ × age group FE | $Y$ | $Y$ |
| Enrollment $t-1$ × country FE | $Y$ | $Y$ |
| Attainment $t$ × country FE | $Y$ | $Y$ |

*Note:* This table shows heterogeneous analysis across countries and ages of disaster effect on enrollment. 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 disaster 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 shock experience, 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 1000 days of life, 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.6: Disaster and enrollment, heterogeneity across gender

| | (1) | (2) |
|---|---|---|
| **Had disaster in recent 12 mo.** | | |
| $\times$ Male | $-0.003$ | $0.056^{**}$ |
| | (0.006) | (0.025) |
| $\times$ Female | $-0.005$ | $0.056^{**}$ |
| | (0.006) | (0.025) |
| **# of mo. with disaster in the first 1000 days** | | |
| $\times$ Male | $-0.002^{***}$ | $-0.002^{***}$ |
| | (0.001) | (0.001) |
| $\times$ Female | $-0.000$ | $-0.000$ |
| | (0.000) | (0.000) |
| Observations | 143645 | 143622 |
| Within country location FE | $Y$ | |
| Country $\times$ cluster FE | | $Y$ |
| Interview year FE | $Y$ | $Y$ |
| Interview month FE | $Y$ | $Y$ |
| Child age FE | $Y$ | $Y$ |
| Enrollment $t-1$ $\times$ age group FE | $Y$ | $Y$ |
| Attainment $t$ $\times$ age group FE | $Y$ | $Y$ |
| Enrollment $t-1$ $\times$ country FE | $Y$ | $Y$ |
| Attainment $t$ $\times$ country FE | $Y$ | $Y$ |

*Note:* This table shows heterogeneous analysis across ages of disaster effect on enrollment corresponded with Equation 2 by interacting disaster shocks with gender. For children in age 5-8, about 55% of them have experienced natural disaster in most recent 12 months, while 59% of children in age 9-12 and in age 13-17 have disaster shock in this time span. The average number of months with disaster in first 1000 days for children in age 5-8, 9-12, and 13-17 is about 2 months, 3 months, and 4 months, respectively. Standard errors, clustered at the within country location level, are reported in parentheses.

Table C.7: Regression of math score on disaster shock

| | (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 1000 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 1000 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 result of Equation 3 using different measures for disaster shock. In each column, four shocks covering one child's disaster exposure history is included representing four time spans: first 1000 days, mid-child life (time between 1000 days of life 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: Disaster and math test score, heterogeneity across country groups

| | (1) | (2) |
|---|---|---|
| **# of mo. with disaster in mid-child life** | | |
| × Pakistan | −0.004 | −0.008 |
| | (0.023) | (0.022) |
| × Bangladesh | −0.054** | −0.061** |
| | (0.024) | (0.025) |
| × Others | 0.034 | 0.033 |
| | (0.027) | (0.028) |
| **# of mo. with disaster in the first 1000 days** | | |
| × Pakistan | −0.093*** | −0.076*** |
| | (0.020) | (0.020) |
| × Bangladesh | 0.025 | 0.019 |
| | (0.031) | (0.031) |
| × Others | 0.033 | 0.046 |
| | (0.030) | (0.032) |
| Observations | 78305 | 78141 |
| Within country location FE | $Y$ | |
| Country × cluster FE | | $Y$ |
| Interview year FE | $Y$ | $Y$ |
| Interview month FE | $Y$ | $Y$ |
| Child age FE | $Y$ | $Y$ |
| Attainment $t$ × country FE | $Y$ | $Y$ |

*Note:* This table shows heterogeneous analysis across countries of disaster effect on math test score. This is corresponded with Equation 3 with interaction between disaster shocks and country groups. The math test score outcome is the absolute test score of each child. The average math test score for children in Pakistan is 10.31 with standard deviation 7.66. The average math test score in Bangladesh is 16.32 and standard deviation is 5.87. For children in countries other than Pakistan and Bangladesh are observed with average math test score 18.7 with standard deviation 4.38. The distribution of math test score across ages and countries is shown in Figure 8. The average number of months covered in mid-life child for all children in Pakistan, Bangladesh, and other countries is 83 months, 89 months, and 77 months, respectively. Standard errors, clustered at the within country location level, are reported in parentheses.

Table C.9: Disaster and math test score, heterogeneity across ages groups and countries

| | (1) | (2) |
|---|---|---|
| **# of mo. with disaster in mid-child life** | | |
| × Pakistan | | |
| × Age 7–9 | −0.045 | 0.015 |
| | (0.070) | (0.073) |
| × Age 10–12 | −0.124** | −0.092** |
| | (0.050) | (0.044) |
| × Age 13–14 | −0.054 | −0.050 |
| | (0.037) | (0.033) |
| × Bangladesh | | |
| × Age 7–9 | −0.153*** | −0.128** |
| | (0.057) | (0.060) |
| × Age 10–12 | −0.030 | −0.020 |
| | (0.030) | (0.031) |
| × Age 13–14 | −0.065** | −0.069** |
| | (0.029) | (0.030) |
| × Other countries | | |
| × Age 7–9 | 0.031 | 0.052 |
| | (0.042) | (0.044) |
| × Age 10–12 | 0.032 | 0.048 |
| | (0.040) | (0.040) |
| × Age 13–14 | 0.032 | 0.048 |
| | (0.042) | (0.042) |
| **# of mo. with disaster in the first 1000 days** | | |
| × Pakistan | | |
| × Age 7–9 | −0.198*** | −0.124** |
| | (0.065) | (0.060) |
| × Age 10–12 | −0.013 | 0.005 |
| | (0.024) | (0.024) |
| × Age 13–14 | −0.090 | −0.069 |
| | (0.056) | (0.060) |
| × Bangladesh | | |
| × Age 7–9 | 0.075 | 0.086 |
| | (0.057) | (0.059) |
| × Age 10–12 | 0.038 | 0.006 |
| | (0.032) | (0.033) |
| × Age 13–14 | −0.012 | −0.002 |
| | (0.031) | (0.033) |
| × Other countries | | |
| × Age 7–9 | 0.017 | 0.027 |
| | (0.029) | (0.029) |
| × Age 10–12 | 0.040 | 0.028 |
| | (0.034) | (0.032) |
| × Age 13–14 | 0.086*** | 0.061* |
| | (0.032) | (0.034) |
| Observations | 78303 | 78139 |
| Within country location FE | *Y* | |
| Country × cluster FE | | *Y* |
| Interview year FE | *Y* | *Y* |
| Interview month FE | *Y* | *Y* |
| Child age FE | *Y* | *Y* |
| Attainment $t$ × country FE | *Y* | *Y* |

*Note:* This table shows heterogeneous analysis across countries and ages of disaster effect on math test score. 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.

Table C.10: Disaster and enrollment, average effects using other disaster intensity types

| | (1) Flood | (2) Severe disaster | (3) Severe flood |
|---|---|---|---|
| Had disaster in recent 12 mo. | −0.012** | 0.003 | 0.002 |
| | (0.005) | (0.008) | (0.006) |
| # of mo. with disaster in the first 1000 days | −0.002*** | −0.002*** | −0.004*** |
| | (0.001) | (0.001) | (0.001) |
| Enrollment in year $t-1$ | 0.386*** | 0.387*** | 0.385*** |
| | (0.012) | (0.012) | (0.012) |
| Attainment at start of $t$ | 0.013*** | 0.013*** | 0.013*** |
| | (0.002) | (0.002) | (0.002) |
| Female | −0.006*** | −0.006*** | −0.006*** |
| | (0.002) | (0.002) | (0.002) |
| Mother is alive | −0.009 | −0.009 | −0.009 |
| | (0.006) | (0.006) | (0.006) |
| Father is alive | 0.012*** | 0.012*** | 0.012*** |
| | (0.004) | (0.004) | (0.004) |
| Mother is alive × living in same HH | 0.025*** | 0.025*** | 0.025*** |
| | (0.005) | (0.005) | (0.005) |
| Father is alive × living in same HH | −0.005** | −0.005** | −0.005** |
| | (0.002) | (0.002) | (0.002) |
| Mother ever educated | 0.041*** | 0.041*** | 0.041*** |
| | (0.003) | (0.003) | (0.003) |
| Mother ever educated × has secondary education | 0.011*** | 0.011*** | 0.011*** |
| | (0.002) | (0.002) | (0.002) |
| Observations | 143645 | 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 | $Y$ | $Y$ | $Y$ |
| Attainment $t$ × age group FE | $Y$ | $Y$ | $Y$ |
| Enrollment $t-1$ × country FE | $Y$ | $Y$ | $Y$ |
| Attainment $t$ × country FE | $Y$ | $Y$ | $Y$ |

*Note:* For the disaster intensity type, we consider type A as any type of disaster, B as only flood, C as severe disasters which is defined as causing more than 50 people dead or injured or 5,000 people affected. Type D combines B and C considering only severe flood. In the main results, we use type A disaster intensity for all time spans. Having various types of disaster intensity provides us the possibility for robustness checks on disaster experience construction.

Table C.11: Disaster and enrollment, heterogeneous effects across age groups using other disaster intensity types

| | (1) Flood | (2) Severe disaster | (3) Severe flood |
|---|---|---|---|
| **Had disaster in recent 12 mo.** | | | |
| × Age 5–8 | −0.019** | 0.019* | 0.045*** |
| | (0.009) | (0.011) | (0.008) |
| × Age 9–12 | −0.014** | −0.004 | −0.017*** |
| | (0.007) | (0.008) | (0.006) |
| × Age 13–17 | −0.003 | −0.008 | −0.025*** |
| | (0.009) | (0.010) | (0.008) |
| **# of mo. with disaster in the first 1000 days** | | | |
| × Age 5–8 | −0.001 | −0.001 | −0.005* |
| | (0.003) | (0.001) | (0.003) |
| × Age 9–12 | −0.003*** | −0.002*** | −0.003*** |
| | (0.001) | (0.001) | (0.001) |
| × Age 13–17 | −0.002*** | −0.003*** | −0.003** |
| | (0.001) | (0.001) | (0.001) |
| Observations | 143645 | 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 | $Y$ | $Y$ | $Y$ |
| Attainment $t$ × age group FE | $Y$ | $Y$ | $Y$ |
| Enrollment $t-1$ × country FE | $Y$ | $Y$ | $Y$ |
| Attainment $t$ × country FE | $Y$ | $Y$ | $Y$ |

*Note:* For the disaster intensity type, we consider type A as any type of disaster, B as only flood, C as severe disasters which is defined as causing more than 50 people dead or injured or 5,000 people affected. Type D combines B and C considering only severe flood. In the main results, we use type A disaster intensity for all time spans. 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 C.12: Disaster and enrollment, heterogeneous effects across gender and age groups using other disaster intensity types

| | (1) Flood | (2) Severe disaster | (3) Severe flood |
|---|---|---|---|
| **Had disaster in recent 12 mo.** | | | |
| × Male | | | |
| × Age 5–8 | −0.019** | 0.015 | 0.036*** |
| | (0.009) | (0.011) | (0.009) |
| × Age 9–12 | −0.022*** | −0.014 | −0.031*** |
| | (0.007) | (0.009) | (0.007) |
| × Age 13–17 | −0.011 | −0.016 | −0.036*** |
| | (0.009) | (0.010) | (0.008) |
| × Female | | | |
| × Age 5–8 | −0.019* | 0.022* | 0.053*** |
| | (0.010) | (0.012) | (0.008) |
| × Age 9–12 | −0.005 | 0.007 | −0.001 |
| | (0.007) | (0.009) | (0.006) |
| × Age 13–17 | 0.005 | 0.003 | −0.011 |
| | (0.009) | (0.010) | (0.008) |
| **# of mo. with disaster in the first 1000 days** | | | |
| × Male | | | |
| × Age 5–8 | 0.002 | 0.001 | −0.001 |
| | (0.003) | (0.002) | (0.003) |
| × Age 9–12 | −0.003*** | −0.003*** | −0.004*** |
| | (0.001) | (0.001) | (0.001) |
| × Age 13–17 | −0.002** | −0.004*** | −0.003** |
| | (0.001) | (0.001) | (0.001) |
| × Female | | | |
| × Age 5–8 | −0.005* | −0.002 | −0.009*** |
| | (0.003) | (0.002) | (0.003) |
| × Age 9–12 | −0.003*** | −0.000 | −0.002* |
| | (0.001) | (0.001) | (0.001) |
| × Age 13–17 | −0.002** | −0.003** | −0.003** |
| | (0.001) | (0.001) | (0.001) |
| Observations | 143645 | 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* | *Y* | *Y* |
| Attainment $t$ × age group FE | *Y* | *Y* | *Y* |
| Enrollment $t-1$ × country FE | *Y* | *Y* | *Y* |
| Attainment $t$ × country FE | *Y* | *Y* | *Y* |

*Note:* For the disaster intensity type, we consider type A as any type of disaster, B as only flood, C as severe disasters which is defined as causing more than 50 people dead or injured or 5,000 people affected. Type D combines B and C considering only severe flood. In the main results, we use type A disaster intensity for all time spans. 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 C.13: Disaster and math test score, average effects using other disaster intensity types

| | (1) Flood | (2) Severe disaster | (3) Severe flood |
|---|---|---|---|
| ***Recent** experience: had disaster* | | | |
| in recent 12 mo. | −0.364 | −0.015 | −0.380 |
| | (0.275) | (0.209) | (0.314) |
| in yr prior 12 mo. ago | 0.016 | 0.213 | −0.058 |
| | (0.254) | (0.204) | (0.188) |
| ***Mid-child life** experience: # of mo. with disaster* | | | |
| (> 1000 days) & (< yr. before last yr.) | −0.022 | −0.009 | 0.013 |
| | (0.027) | (0.022) | (0.036) |
| ***Early-life** experience: # of mo. with disaster* | | | |
| in the first 1000 days | −0.065*** | −0.008 | −0.047 |
| | (0.024) | (0.022) | (0.033) |
| Female | −0.417*** | −0.419*** | −0.418*** |
| | (0.061) | (0.061) | (0.061) |
| Mother is alive | 0.321** | 0.324** | 0.323** |
| | (0.160) | (0.160) | (0.160) |
| Father is alive | 0.226** | 0.225** | 0.226** |
| | (0.105) | (0.105) | (0.105) |
| Mother is alive × living in same HH | 0.057 | 0.056 | 0.056 |
| | (0.080) | (0.080) | (0.080) |
| Father is alive × living in same HH | −0.217*** | −0.216*** | −0.216*** |
| | (0.061) | (0.061) | (0.061) |
| Mother ever educated | 1.337*** | 1.343*** | 1.341*** |
| | (0.082) | (0.082) | (0.082) |
| Mother ever educated × has secondary | 1.000*** | 0.997*** | 0.998*** |
| | (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* |
| Attainment $t$ × country FE | *Y* | *Y* | *Y* |

*Note:* For the disaster intensity type, we consider type A as any type of disaster, B as only flood, C as severe disasters which is defined as causing more than 50 people dead or injured or 5,000 people affected. Type D combines B and C considering only severe flood. In the main results, we use type A disaster intensity for all time spans. 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 C.14: Disaster and math test score, heterogeneous effects across age groups using other disaster intensity types

| | (1)<br>Flood | (2)<br>Severe disaster | (3)<br>Severe flood |
|---|---|---|---|
| **# of mo. with disaster in mid-child life** | | | |
| × Age 7–9 | 0.016 | −0.006 | 0.069 |
| | (0.050) | (0.039) | (0.061) |
| × Age 10–12 | −0.034 | −0.019 | 0.021 |
| | (0.042) | (0.026) | (0.051) |
| × Age 13–14 | −0.030 | −0.026 | 0.023 |
| | (0.036) | (0.026) | (0.047) |
| **# of mo. with disaster in the first 1000 days** | | | |
| × Age 7–9 | −0.087 | −0.031 | −0.052 |
| | (0.053) | (0.029) | (0.059) |
| × Age 10–12 | −0.001 | 0.016 | −0.002 |
| | (0.027) | (0.024) | (0.041) |
| × Age 13–14 | −0.023 | −0.028 | −0.040 |
| | (0.031) | (0.030) | (0.040) |
| Observations | 78303 | 78303 | 78303 |
| Within country location FE | $Y$ | $Y$ | $Y$ |
| Interview year FE | $Y$ | $Y$ | $Y$ |
| Interview month FE | $Y$ | $Y$ | $Y$ |
| Child age FE | $Y$ | $Y$ | $Y$ |
| Attainment $t$ × country FE | $Y$ | $Y$ | $Y$ |

*Note:* For the disaster intensity type, we consider type A as any type of disaster, B as only flood, C as severe disasters which is defined as causing more than 50 people dead or injured or 5,000 people affected. Type D combines B and C considering only severe flood. In the main results, we use type A disaster intensity for all time spans. 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 C.15: Disaster and math test score, heterogeneous effects across gender using other disaster intensity types

| | (1) Flood | (2) Severe disaster | (3) Severe flood |
|---|---|---|---|
| **# of mo. with disaster in mid-child life** | | | |
| × Male | −0.018 | −0.013 | 0.022 |
| | (0.030) | (0.024) | (0.038) |
| × Female | −0.027 | −0.002 | 0.003 |
| | (0.028) | (0.022) | (0.036) |
| **# of mo. with disaster in the first 1000 days** | | | |
| × Male | −0.069*** | −0.017 | −0.064* |
| | (0.026) | (0.024) | (0.035) |
| × Female | −0.061** | 0.003 | −0.030 |
| | (0.026) | (0.022) | (0.035) |
| 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* |
| Attainment $t$ × country FE | *Y* | *Y* | *Y* |

*Note:* For the disaster intensity type, we consider type A as any type of disaster, B as only flood, C as severe disasters which is defined as causing more than 50 people dead or injured or 5,000 people affected. Type D combines B and C considering only severe flood. In the main results, we use type A disaster intensity for all time spans. 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.

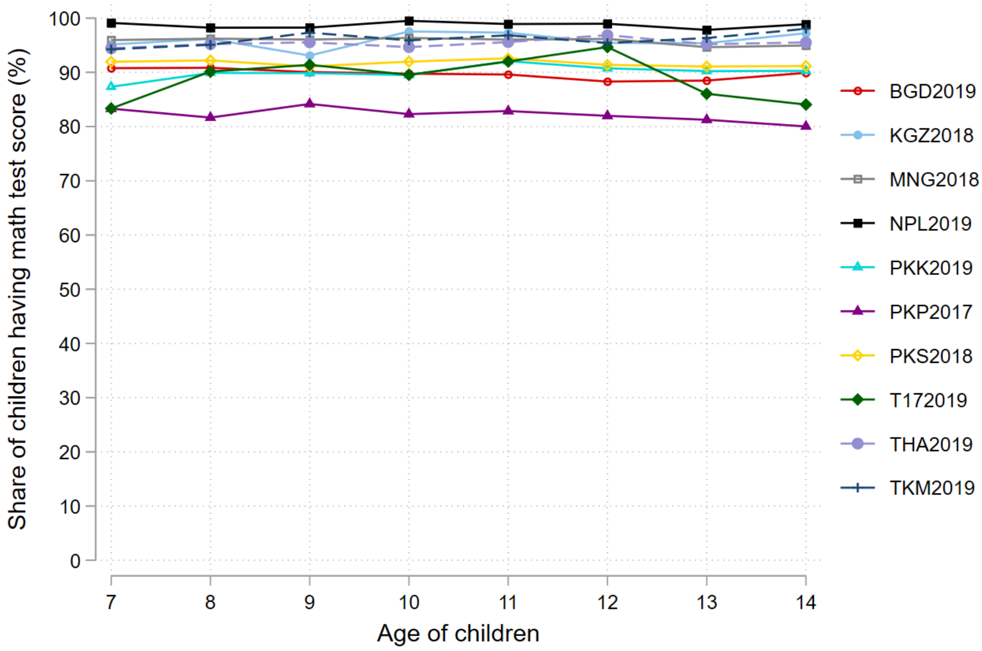
Table C.16: Disaster and math test score, heterogeneous effects across gender and age groups using other disaster intensity types

| | (1) Flood | (2) Severe disaster | (3) Severe flood |
|---|---|---|---|
| **# of mo. with disaster in mid-child life** | | | |
| × Male | | | |
| × Age 7–9 | 0.013 | −0.011 | 0.073 |
| | (0.052) | (0.042) | (0.064) |
| × Age 10–12 | −0.011 | −0.014 | 0.047 |
| | (0.044) | (0.028) | (0.054) |
| × Age 13–14 | −0.044 | −0.034 | 0.010 |
| | (0.040) | (0.027) | (0.050) |
| × Female | | | |
| × Age 7–9 | 0.018 | 0.003 | 0.067 |
| | (0.052) | (0.040) | (0.066) |
| × Age 10–12 | −0.060 | −0.021 | −0.010 |
| | (0.044) | (0.027) | (0.051) |
| × Age 13–14 | −0.017 | −0.016 | 0.032 |
| | (0.037) | (0.026) | (0.046) |
| **# of mo. with disaster in the first 1000 days** | | | |
| × Male | | | |
| × Age 7–9 | −0.095* | −0.047 | −0.070 |
| | (0.053) | (0.031) | (0.060) |
| × Age 10–12 | −0.003 | 0.011 | −0.031 |
| | (0.032) | (0.029) | (0.047) |
| × Age 13–14 | −0.008 | −0.031 | −0.025 |
| | (0.045) | (0.038) | (0.052) |
| × Female | | | |
| × Age 7–9 | −0.076 | −0.015 | −0.035 |
| | (0.059) | (0.030) | (0.063) |
| × Age 10–12 | 0.004 | 0.023 | 0.028 |
| | (0.033) | (0.025) | (0.046) |
| × Age 13–14 | −0.037 | −0.023 | −0.054 |
| | (0.040) | (0.035) | (0.050) |
| Observations | 78303 | 78303 | 78303 |
| 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* |
| Attainment $t$ × country FE | *Y* | *Y* | *Y* |

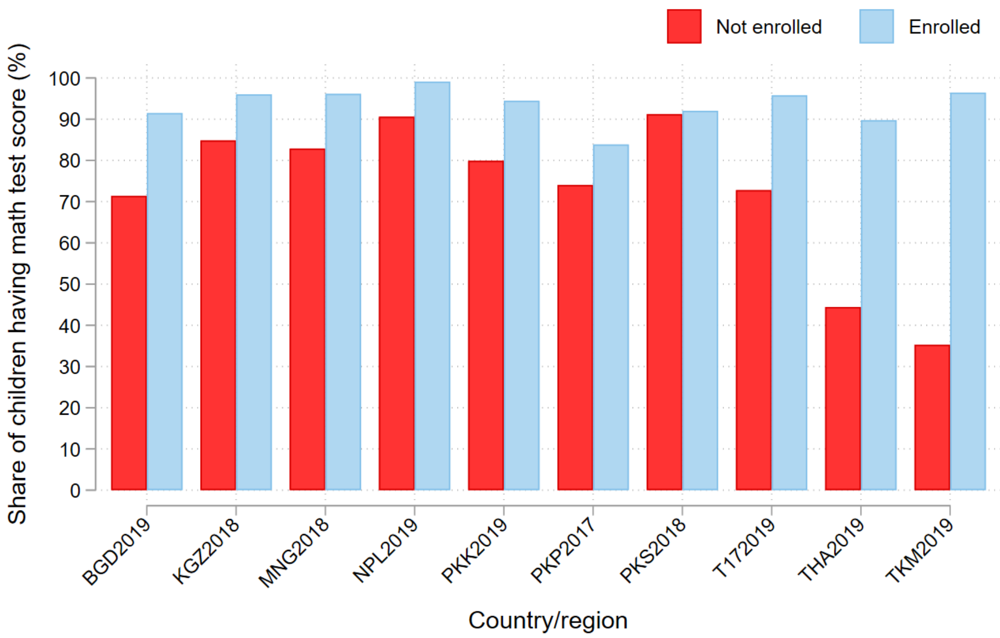
*Note:* For the disaster intensity type, we consider type A as any type of disaster, B as only flood, C as severe disasters which is defined as causing more than 50 people dead or injured or 5,000 people affected. Type D combines B and C considering only severe flood. In the main results, we use type A disaster intensity for all time spans. 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 C.1: Math Test Sample Size

(a) Math Test Sample Size by Ages and Countries



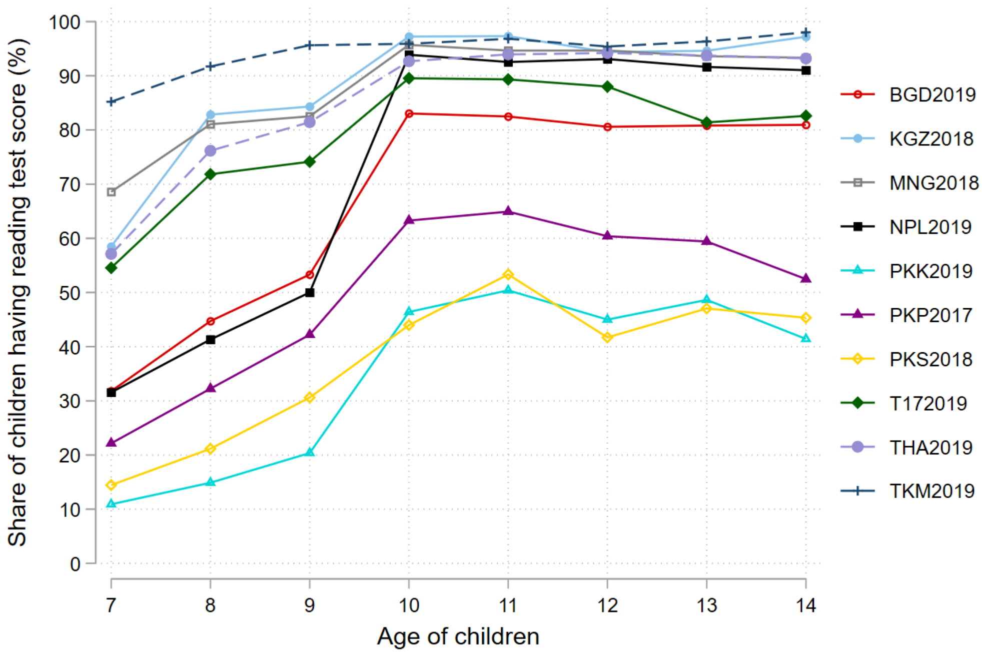

(b) Math Test Sample Size by Enrollment Status in Current Year Across Countries



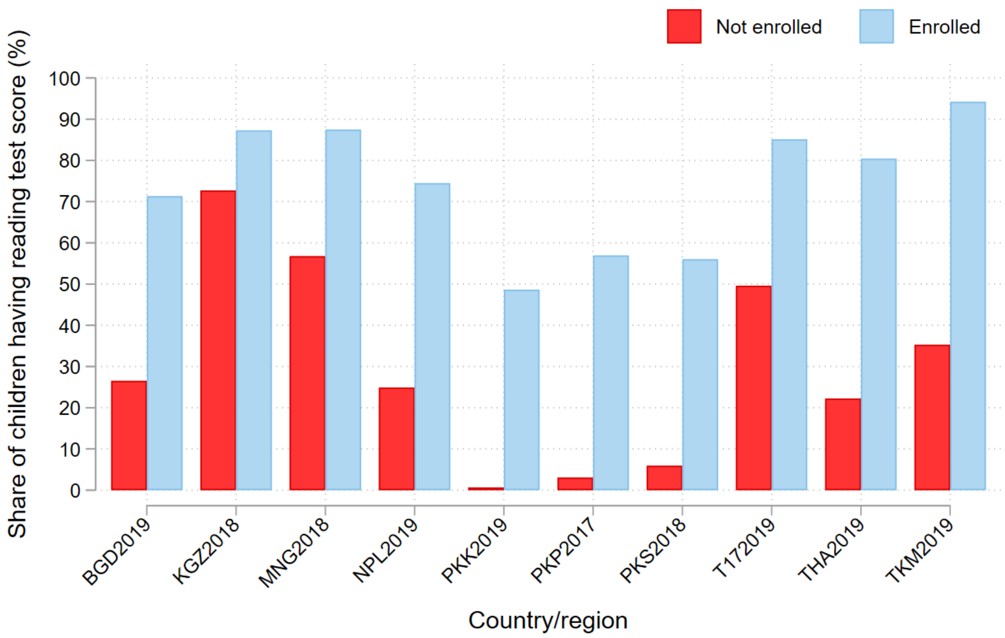

*Note:* Fractions show share of sample by age and country reporting math test score, consistent share across ages, some variation across countries. We notice whether the child has Math test Score is related to if she is enrolled in school in the current period. We find much larger share with math test 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** Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **KGZ**).

Figure C.2: Reading Test Sample Size

(a) Reading Test Sample Size by Age

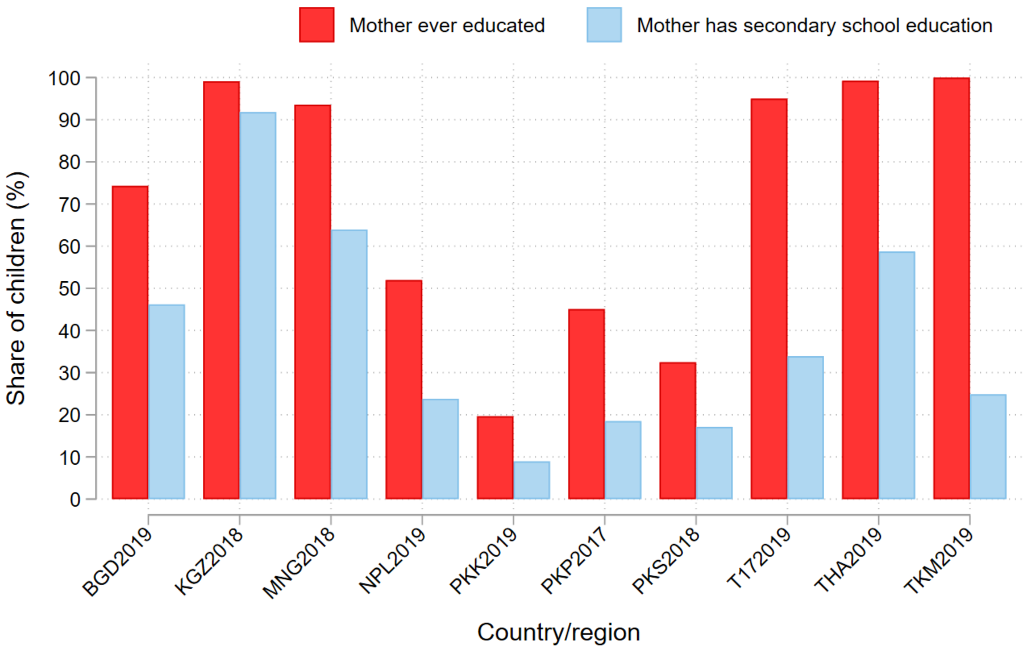



(b) Reading Test Sample Size by Enrollment Status Across Countries



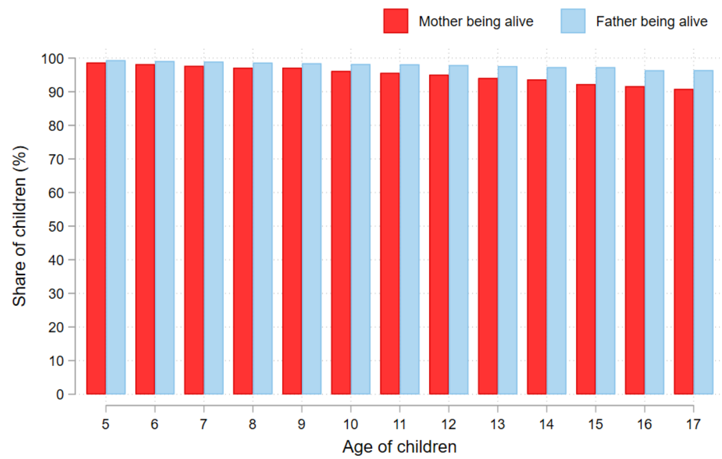

*Note:* Fractions show share of sample by age and country reporting reading test score, consistent share across ages, some variation across countries. We notice whether the child has reading test Score is related to if she is enrolled in school in the current period. We find much larger share with reading 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** Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **KGZ**).

Figure C.3: Share of Children Whose Mother Has Some Education

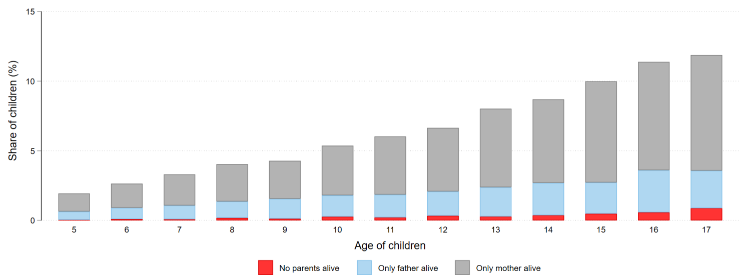



*Note:* This table show (1) share of children whose mother has had any kind of education (2) share of children whose mother has secondary school education by countries. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP**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

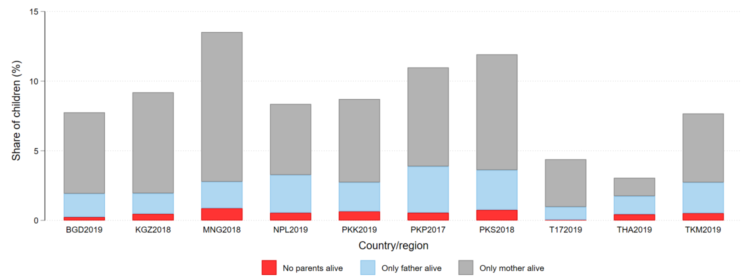
Figure C.4: Share of Children with Mother or Father Alive by Ages




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



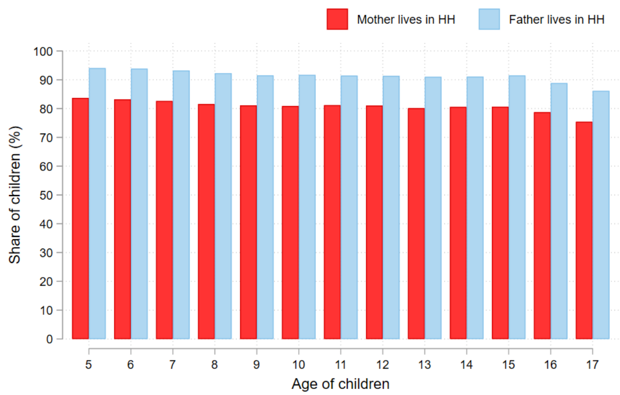

(b) Share of Children with Both or One Parent Alive by Ages



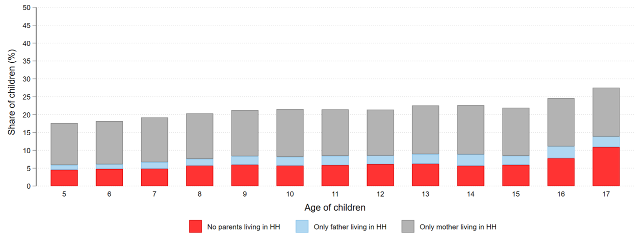

(c) Share of Children (Age $\geq$ 12) with Both or One Parent Alive by Countries

*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.

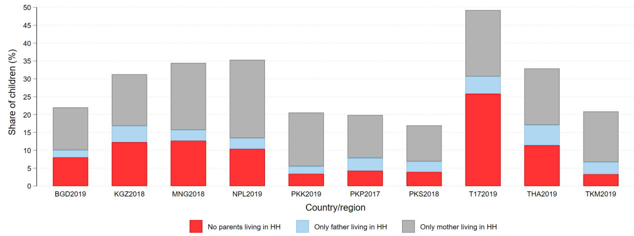
Figure C.5: Share of Children Living with Parents




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




(b) Share of Children Living with Both or One Parent by Ages

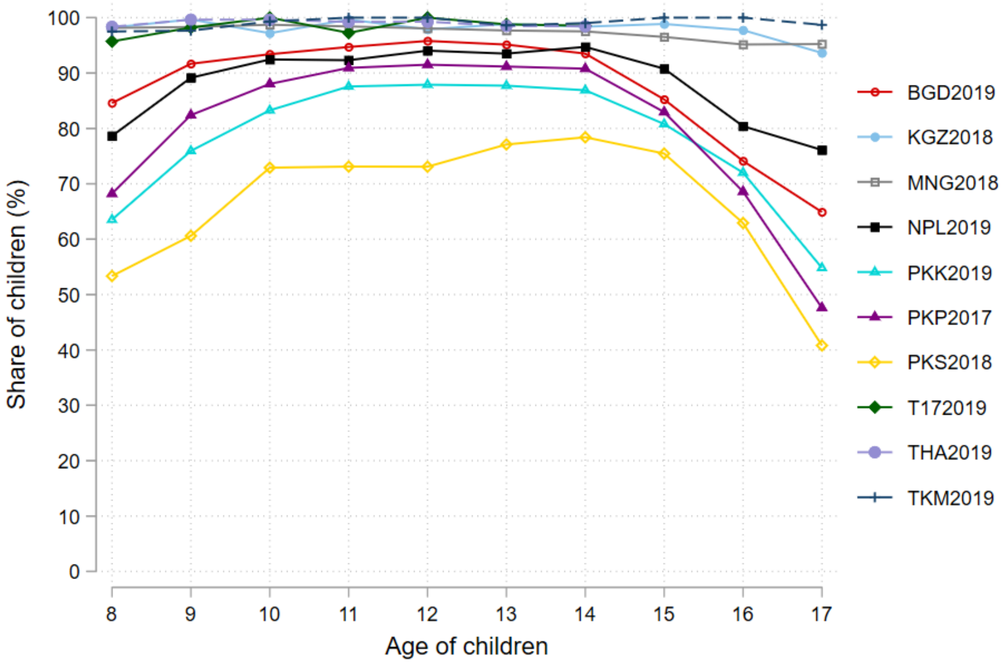



(c) Share of Children (Age $\geq$ 12) Living with Both or One Parent by Countries

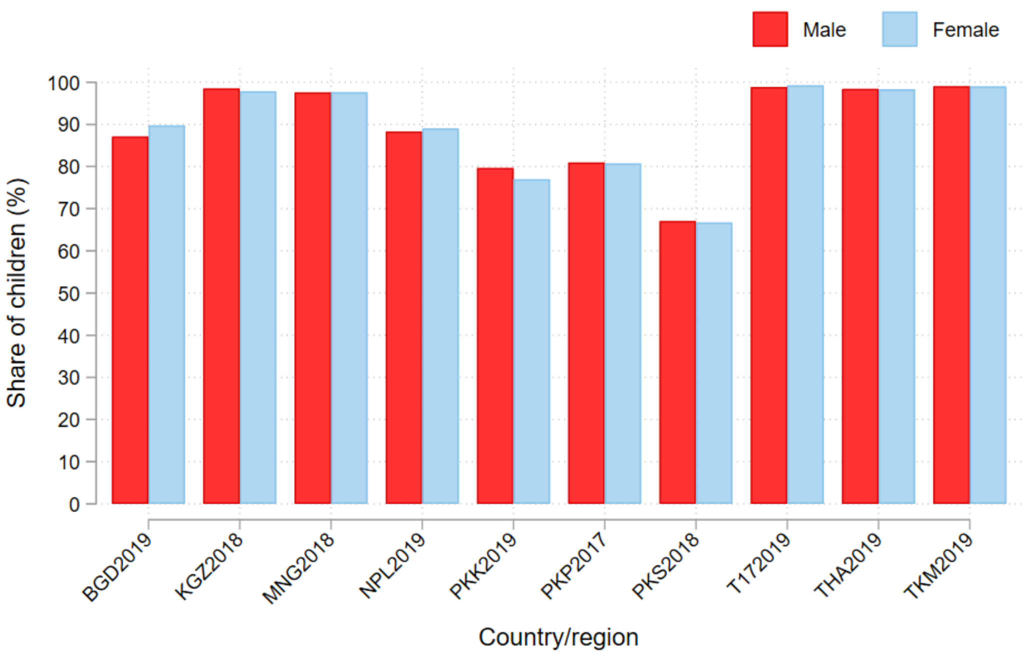
*Note:* Panel (a) shows the share of children living with either mother or father by ages. Panel (b) and (c) show the share of children living with both parents or one of them by ages. The four categories include living with both parents (not included in the bar), with just mother, with just father,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

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

(a) Progression Rate in Last Year by Ages and Countries



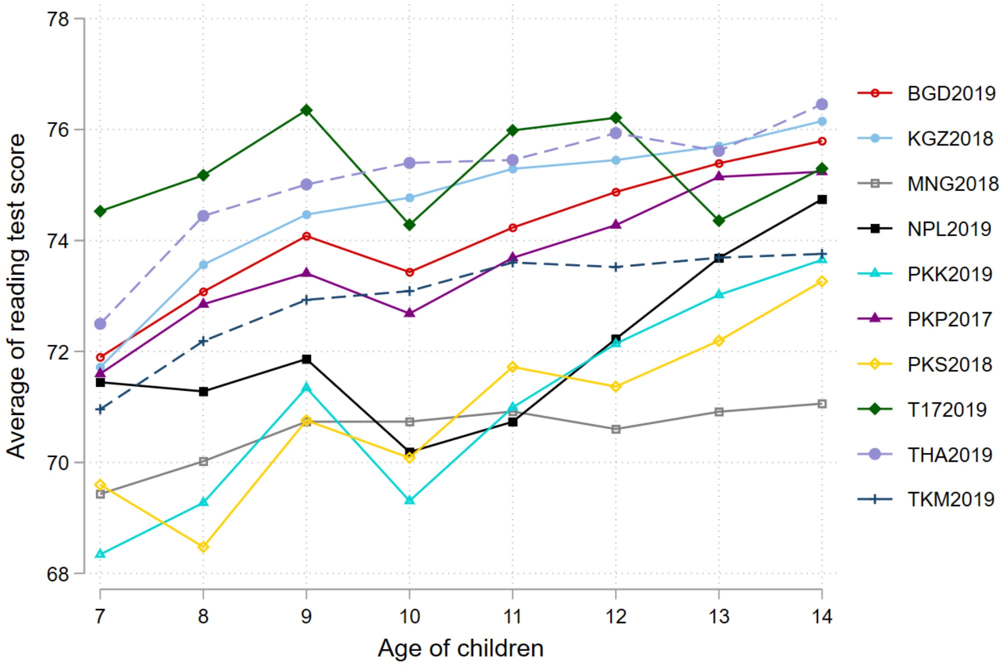

(b) Progression Rate in Last Year by Gender and Countries ($\geq$ age 8)



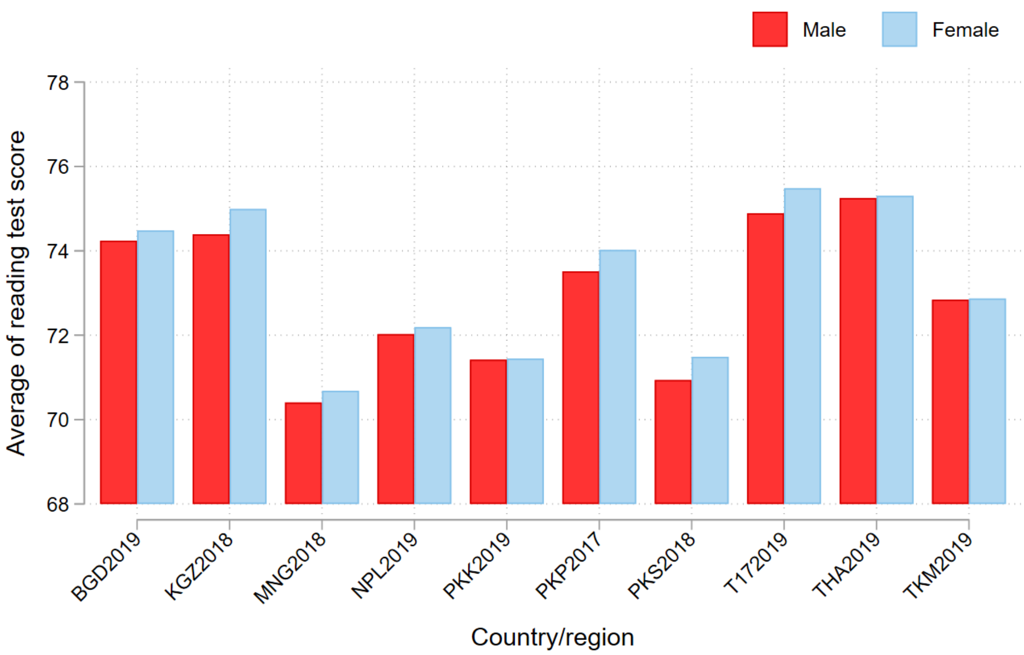

*Note:* The table shows progression rates. Progression is equal to 1 if a child attends a grade and successfully completes the grade, leading to an increase in grades completion by 1 years. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber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

Figure C.7: Distribution on 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** Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **KGZ**).