

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

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Abstract

We estimate natural-disaster impacts on children's school enrollment and math skills and their heterogeneities along with age and gender 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 of life, the most recent years, and the time in between. Results show significant negative effects of early-life natural disaster exposure on enrollment and math skills; weaker or no effects of recent or mid-child life disaster exposures; persistent negative effects of early life exposure on enrollment through school-going ages; variable age patterns of enrollment and learning effects of exposure across countries; boys' enrollments are more negatively affected but girls' math test scores are more negatively affected by early-life natural disaster exposure.

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

JEL: I24, I25, Q54, Q56

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1 Introduction

Between 1970 and 2019, the United Nations reports that climate change and extreme-weather events 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, climate change will continue to lead to increased frequency and severity of natural disasters such as floods, drought, and extreme weather (Ipcc 2022). Climate-change-induced disasters pose a particularly serious threat 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, climate, 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 disaster shocks. 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 climate crisis (UNICEF 2021b). Studies of natural disasters’ effects on children have focused on tracing the impacts of a specific large-scale disaster (Cho and Kim 2023; Hadiman and Djameluddin 2022; Tian, Gong, and Zhai 2022; Ciraudo 2020; Gibbs et al. 2019; De Vrejer, Guilbert, and Mesple-Soms 2015; Cas et al. 2014). Most of these studies focus on the effect of natural disasters on child development through their health status, not educational outcomes, such as the studies on fetal-origins hypothesis in short-run 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’ anthropometric outcomes such as fetal loss and birth weights are found to be negatively affected by *in utero* exposure to natural disasters or extreme climate 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 argued 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), another study showing that lower educational attainment in adulthood comes with high-intensity exposure to the 1976 Tangshan earthquake (Tian, Gong, and Zhai 2022), and paper revealing the lower cognitive score in chil-

1. There are limited papers on broad groups of disasters. Those using multiple types or groups of disasters, moreover, do not focus on educational outcomes in developing countries. Oppen, Park, and Husted (2023) use data from the United States and find that natural disasters impact a region’s human capital both via reductions in learning for students who stay in school and in the grades of schooling completed. Simeonova (2011) also uses US data and Currie and Rossin-Slater (2013) study groups 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 by type of disasters.

dren in age 0-2 who experienced the 2006 Yogyakarta earthquake (Hadiman and Djameluddin 2022). Cirauo (2020) tracks the academic performance of a cohort in Chile affected in early life by the 1985 earthquake and De Vreyer, Guilbert, and Mesple-Soms (2015) show negative educational outcomes after large income shocks related to the 1987-89 locust plague in Mali using census data. Gibbs et al. (2019) find that academic performance was reduced in schools with higher exposure to a major bushfire in Australia.

Impacts of climate 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 death, 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). Recent work by Adhvaryu et al. (2024) shows that the 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 affects physical health.

While the aforementioned reasons would tend to reduce enrollment under disasters, for some children, the effects might also go in the opposite direction: schools and school-based facilities might be a potential place 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.

In this paper, we provide one of the first cross-country and all-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 survey data 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 from 1998 to 2019 in seven Asian countries from EM-DAT, which includes floods, storms, droughts, earthquakes, and extreme temperatures. Exploiting variations in MICS-survey locations, variations in location-specific

2. The impact of disruptions on school attendance and how to strengthen the resilience of school system 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 intergenerational transmission of early-life exposure. It also not just focuses on one single event, but various natural disasters. It studies human capital outcomes in adulthood, such as years of education, employment disabilities, and wealth for the first generation, and enrollment, years of education, and child labor for the second generation. Our paper builds on this emphasizing educational outcomes in childhood, particularly the MICS-administered math test score, which serves as a valuable measure for cognitive skills.

survey timing, as well as variations in child ages 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 ⁴.

Short-term enrollment effects of disasters could lead to long-term impacts on human-capital development and accumulation for children. Hence, we investigate the impact of exposure history to natural disaster on human-capital accumulation. This means we consider not only the impacts of recent disaster shocks but also of early-life disasters on human-capital accumulation. Children experience poorer health and educational outcomes in the long run if exposure 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 exposure have negative effects on educational or economic performance later in life (Andrabi, Daniels, and Das 2021; Charil et al. 2010; Fuller 2014). In addition, 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 as one possibly critical life-cycle stage on the period from conception until age two (first 1000 days) to construct early-life shocks.⁵ Abnormal health status in early life could in the longer run exert negative effects on subsequent IQ and lower cognitive development as well as increase the cost of children attending schools compared to their peers as they may need more medical attention and miss classes more.

We estimate the impacts of natural disasters on school enrollment and human capital accumulation as measured by learning 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 unobserved time-varying and location-specific 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 impact of disaster shocks on enrollment. Specifically, we augment an enrollment-decision equation that is a function of current 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 country while controlling for parental conditions. In our second empirical model, we specify an important

4. Despite considering all types of disasters, which is used to construct type-A disaster shocks 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).

indicator of educational achievement—MICS-administered math test scores—as the output of human-capital-production functions (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 disaster inputs over the life for 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 the most recent two years, and the most recent two years. To the best of our knowledge, this is the first paper to jointly consider these correlated histories of disaster exposures.

For the effects of natural-disaster shocks on enrollment status, we find a significant negative effect of early-life disaster exposure, but weaker or no corresponding effects for 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, which is found to affect boys rather than girls. The relation between exposure to natural disasters and math-test scores is also weak for recent shocks yet strong for exposure in early life. Although the impact on school enrollment is greater for boys than girls, the cognitive performances measured by math tests of girls are harder hit than that of boys both in the younger and older cohort (age 7-9 and age 13-14). Age patterns of learning effects of disaster exposure differs 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 are underestimated.

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 household and individuals. 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 enrollment 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 on which we focus. MICS6 also provides information that we use as controls and to explore heterogeneities on the children (e.g., gender, ages, schooling attainment prior to the surveys) and on 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 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 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 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

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.

(Kahn 2005), 89 countries (Skidmore and Toya 2002), 108 countries (Felbermayr and Gröschl 2014), and for 109 countries (Noy 2009) over several decades. The effects of disasters on firm-level outcomes including employment, asset accumulation, and productivity is 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).

In our raw data spreadsheet file, each row is one disaster and columns are information associated with this disaster. Each disaster has same identifier and when one disaster affects several countries, it is recorded several times. Variables available 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 name, ISO Code, 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 districts 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, 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 being educated, and an indicator of having secondary education.

2.3.2 Educational Outcomes

The educational outcomes that we consider are school enrollment and math learning skills for children ages 7 to 14.⁷ We show the average enrollment rate at the regional level⁸ for each country in Table 1. Math learning skills are assessed for children aged 7 to 14 years old by tests administered by the interviewers. 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 numeracy 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. We first check the availability of test scores for each child as there is a chance that the child being able to take and complete the test itself shows cognitive skills development. Then we construct the total test score for math as a measure of cognitive skills.

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 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

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 current place. There are several reasons mothers’ migratory information may not be available. First, Pakistan Khyber Pakhtunkhwa Province (denoted as "PKK") women file does not contain migratory variables. Secondly, only women aged 15-49 are surveyed separately. The natural mothers of children in 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

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 name of second-level administrative division (districts) as current location for mothers which is also what we know for children. But we only observe first-level administrative division (division) for prior location of mothers. For Kyrgyzstan, we know first-level administrative location (oblast) for both current and prior locations of mothers. For Mongolia, first-level administrative location (aimag) is observed for both current and prior location of mothers, but not for children. For Nepal, first-level administrative location is collected for both mothers and children. For Pakistan, like Bangladesh, it is observed the second-level administrative location (district) for current location of mothers and children. But the prior location information is only at first administrative level which is much larger. For Thailand, there is also finer information for current location of mothers (region and changwat), but only region names for prior location. For Turkmenistan, first-level administrative (region or province) location names are collected for current and prior location of mothers.

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 that 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 date and age 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, $DI_{il,mo}^p$. It is one if location l in month mo has experienced the type p intensity of disaster shock and zero otherwise. 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, $DI_{il,mo}^p$ is counted as one as well. Then, by calculating $DM_{il,j}^p$, 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 $DB_{il,j}^p$.

$$DM_{il,j}^p = \sum_{mo=\text{start mo. of } j}^{\text{end mo. of } j} DI_{il,mo}^p \quad (1)$$

$$DB_{il,j}^p = 1\{DM_{il,j}^p \geq 1\}$$

Critical Periods in the Life-Cycle. 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 survey month.

This is feasible as interview year and month and birth year and month are available for all children in our MICS sample.¹⁰ The earliest year of birth for a child in these samples was 1999. When we track the EM-DAT disasters from 1998 to 2019, there are in total 509 disasters that happened in that period. All of them except three 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 devine type A to include any type of disaster, B to include only floods, type 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 intensity provides us the possibility for robustness checks on disaster experience construction, which we explore in Appendix C.

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 dates are not observed for all children and starting and ending dates of disasters generally are not recorded making it difficult to match disasters with individuals' life cycles at the date level.

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 5 to 17 years-of-age module from the MICS sixth round. 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 that because only children aged 7 to 14 years participate in the foundational learning assessment module of the survey subject to their availability at home as well as parental consents. In Table 1, we show that the whole sample is collected between 2017 to 2019. Each country is associated with geo-identifier at a different administrative level. For example, children from Bangladesh are observed with which district (administrative level two) they are living in while we know which oblast (administrative level one) children from Kyrgyzstan 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 distribution of the sample 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 father’s age is on average 6 years greater than mother’s age, and the rate of father ever-educated is slightly higher than the same rate for mothers. But it is also noticeable that father information is collected less than that of mother. 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 mother’s educational level 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 share 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.

11. According to a report of Pakistan from DHS (National Institute of Population Studies and ICF 2019), half of ever-married women age 15-49 have no education, and half of children under 5 have mothers without education. This share can be lower if mothers are considered as women with no education have 1.6 more children than women with higher education.

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 enrollment 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 enrollment compared to boys is higher in Bangladesh compared to most countries and lowest in the Pakistan provinces. Enrollment in the current year as well as the preceding year goes up for children up to 10 years of age and then declines for older ages in all countries. We also present in Figure 4 the shares of children who have ever been enrolled in school, which is increasing with age. This rate reaches close to 100 percent of the sample 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 current age. 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. If we look at children 15-17 years of age, girls outperform boys in Bangladesh, Kyrgyzstan, Mongolia.

Test Scores. Children's foundational cognitive skills are measured by math test scores. Average math skill test results by age and country are shown in Table 3 and Figures 8. Aggregate math scores denoting math skills differ substantially across countries with children in Bangladesh 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 a shared high average score trend across age groups. Children from Nepal and Bangladesh have medium levels of average performance and a sharper increase 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 EM-DAT and MICS 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 all

the seven countries experienced at least one disaster. The share of children experiencing any disasters in the 10 years prior to most recent year is 77%, meaning that more than two thirds of locations in our sample in those location-specific 10 years have been hit by at least one disaster.

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. Turkmenistan is not listed here because there are no disasters recorded for Turkmenistan during the spans of time we are considering.

Additionally, we show in Figure 9 the shares of location/months experiencing disasters of different types by calendar months and locations. The results shows more location/months with disaster 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 enrollment 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 effects modifiers. 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). We use separate letters to denote different educational outcomes because for each outcome, the disaster shock that has potential impact on it is constructed differently based on which time span to be considered.

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 have 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 History to Disaster Shocks. In models of children’s schooling enrollment, households make binary schooling enrollment decisions given trade-offs between going to school and alternatives of children staying at home or working (Attanasio, Meghir, and Santiago 2012; Todd and Wolpin 2006; Casco 2022). Without enrollment, the child can not 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 decision (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' decision for enrollment.

In this paper, we estimate a reduced-form model of enrollment decisions as a function of child age, existing 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 decision.

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 progression. Our estimation strategy is on 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 comes from the variation in disaster exposure history. 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 this period has been found to be related to later-life health conditions (Maccini and Yang 2009). Disaster shocks exposure in early childhood might have had formative impacts on the cognitive and non-cognitive skills as well as health status for the child. These underlying characteristics of the child, which can not be fully captured by current attainment and prior enrollment, might impact the expected gains from additional years of education 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 the enrollment decision.

To analyze the relationship between enrollment and disaster experiences, we estimate

the below dynamic equation with lagged dependent variable for enrollment:

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

where $\text{TimeSpan} = \{m12to1, first1000days\}$ with $m12to1$ 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 received 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 initial shock received and we allow for this initial shock to have continued effects on enrollment status through both β_{m12to1} and $\beta_{first1000days}$. With the incorporation of the initial shock into the estimation equation, we introduce the possibility of heterogeneous non-proportional initial effects on the current enrollment status $E_{il,t}$. Our underlying assumption posits that over time (t increasing), there is a cumulative effect from the history of shocks, although the impact of the initial shock is accorded greater significance. In this setting, if we find a negative coefficient $\beta_{first1000days}$, then the regression results would provide a lower bound of the true effects.

We control for a vector X of observed individual and parental characteristics including parental ages, mother’s education, whether the child resides with parents, and whether parents are alive. Additionally, we control for sub-national location fixed effects μ_l , which are at the same level (or lower) of geographical aggregation as the disaster variables, child-age fixed effects $\mu_{g_i(t)}$, and also survey-time fixed effects, μ_t .¹²

Controlling for these fixed effects and observed characteristics is critical for capturing the causal effects of disasters on enrollment. 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 exposure within location, and the latter generates differences across children in life-cycle exposure to disaster within location and survey month. Furthermore, our year and calendar timing fixed effects pick up possible correlations between disaster and enrollment due to within-year seasonality patterns and shifts in 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

12. We control for survey year \times 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.

functions (Todd and Wolpin 2003; Hanushek and Rivkin 2012). The inputs to the production function includes 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, and 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 exposure 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 achievement tests using the following specification:

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

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

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 $\beta_{g_i(m)}^j$:

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

where $\beta_{g_i(m)}^j$ 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 history within location and across individuals. In practice, because conditional on location and age jointly, there are no variations in child exposure history, we can not estimate Eq. (4) with separate $\beta_{g(i,m)}^j$ 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 being educated ever and if mother has secondary education. 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 enrollment, but no significant relationship between experiencing EM-DAT disaster in the most recent year and enrollment. 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 average of 3.0 months and standard deviation of 3.7 months), which correspond to a slightly less than 1 percentage point reduction in enrollment between p10 to p90 exposure to early-life disasters on school enrollment.

Following our discussions of the enrollment decision model, in all columns of Table 5, we include lagged enrollment 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 enrollment. 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 enrollment as well as attainment by age and country fixed effects, there is still strong and positive effects of lagged enrollment on current enrollment.

We also find consistent patterns of relationships between child, parental, and household characteristics and enrollment from columns 2 and 3 of Table 5. Specifically, from column

three, aggregating across countries and ages, we find girls have 0.6% lower enrollment than boys. We also find that having a mother who has had any prior education increases enrollment by 4.1%, and having a mother with secondary education increases enrollment by an additional 1.1%. Interestingly, we find that having a mother who is living in the same household increases enrollment 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 enrollment 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 disaster doubles the magnitude of the estimated effects of early-life exposure on enrollment 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 enrollment in the current year for all children between age 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 enrollment this year 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.¹³ 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 primary school cycle lasting 4 years. In Thailand, elementary school encompasses children aged

13. 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.

6-12. In Turkmenistan, the official primary school entrance age is 6 and 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 secondary 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 gender.

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 focus 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 enrollment is 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-Soms 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, 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 disaster might see increased enrollments post disaster. As children age, the effects of early-life disaster exposures on enrollments appears to be strongly significant negative, especially for boys. Boys age 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 turn 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 point 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 enrollment for children between age 9 to 12 but not the recent experiences. In contrast, between ages 13 to 17, having experienced disaster in the past year reduces enrollment by 2.7 percentage points, and having an additional month of early exposure reduces enrollment by 0.3 percentage point. For children between ages 5 to 8, we find significant positive impacts in Bangladesh on enrollment from recent shocks.

Results for heterogeneous effects of disaster exposure on enrollment 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 relationship between early exposure and enrollment 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 exposure 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.¹⁴ 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 score scales (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 a consistent result of weak and insignificant effects of recent disasters on math scores, but significant effects of disaster 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 exposure reduces test score strongly significantly by 3.1 percentage points. Estimates from column (4) using MICS-cluster fixed effects show similar finding with slightly smaller magnitudes of impacts.

We also find consistent patterns of relationships between child, parental, and household characteristics and enrollment 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

14. 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.

has had any prior education increases scores, and having a mother with secondary education raises the math score further. Additionally, having a mother who is alive has a positive effect on the test score. In contrast, having a father who is alive but not living with the household increases the child’s test score.

The estimated average effects of disaster exposure on math skills using other disaster intensity types are shown in C.13. There are no significant effects from disaster exposure 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 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 correlation between height and test scores in both developing and developed countries is 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. However, children in both Pakistan and Bangladesh are affected by mid-life disaster shock, 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 in our results is that we do not capture disaster history 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 a much lower rate of taking the test. Given our prior results on the impact of disaster on enrollment, this could lead to potential selection bias.

Table C.14, C.15, and C.16 present the heterogeneous effects of disaster exposure on math-test scores using other intensity types across ages or genders, separately or jointly. Overall, there are weak or no effects from recent exposure to natural disasters regardless of the types of disaster intensity, while there are significantly negative effects from early-life exposure 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 climate 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 previous to 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. 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

enrollment 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, while we observe a pattern difference by gender. Although boys are vulnerable in terms of school enrollment to having experienced natural disasters in early life, girls' performance on MICS-administered math tests is harder hit by early-life natural disaster exposure 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 attendance 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	9	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					
<i>Had recent disaster (DB_A) ...</i>					
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
<i>Had disaster at least once in location-specific disaster history (DB_A) ...</i>					
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
<i>Had disaster at least once given child life-cycle-specific disaster history (DB_A) ...</i>					
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

<i>Children who had any disaster (DB_A) ...</i>	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). In Thailand, only children up to age 14 are surveyed. The mid-child life is defined as the period between the first 1000 days of life and two years prior survey month.

Table 5: The effects of disasters on enrollments

	(1)	(2)	(3)
Had disaster in recent 12 mo.	−0.003 (0.006)	−0.002 (0.006)	−0.004 (0.006)
# of mo. with disaster in the first 1000 days	−0.002*** (0.000)	−0.002*** (0.000)	−0.001** (0.000)
Enrollment in year $t - 1$	0.648*** (0.010)	0.641*** (0.010)	0.388*** (0.012)
Attainment at start of t	0.025*** (0.001)	0.024*** (0.001)	0.012*** (0.002)
Female		−0.015*** (0.002)	−0.006*** (0.002)
Mother is alive		−0.015** (0.006)	−0.009 (0.006)
Father is alive		0.013*** (0.004)	0.012*** (0.004)
Mother is alive \times living in same HH		0.029*** (0.005)	0.025*** (0.005)
Father is alive \times living in same HH		−0.005** (0.002)	−0.005** (0.002)
Mother ever educated		0.037*** (0.003)	0.041*** (0.003)
Mother ever educated \times has secondary education		0.004** (0.002)	0.011*** (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 $t - 1 \times$ age group FE			Y
Attainment $t \times$ age group FE			Y
Enrollment $t - 1 \times$ country FE			Y
Attainment $t \times$ 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.		
× Age 5–8	0.008 (0.010)	0.069*** (0.025)
× Age 9–12	−0.009 (0.006)	0.050** (0.025)
× Age 13–17	−0.012 (0.009)	0.046* (0.027)
# of mo. with disaster in the first 1000 days		
× Age 5–8	0.001 (0.001)	0.001 (0.001)
× Age 9–12	−0.002*** (0.000)	−0.002*** (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 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 (0.009)	0.072*** (0.025)
× Age 9–12	−0.010 (0.007)	0.049* (0.025)
× Age 13–17	−0.017 (0.010)	0.041 (0.027)
× Female		
× Age 5–8	0.003 (0.010)	0.064** (0.025)
× Age 9–12	−0.009 (0.006)	0.051** (0.025)
× Age 13–17	−0.008 (0.009)	0.051* (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*** (0.001)	−0.003*** (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 heterogeneous 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)
<i>Recent experience: had disaster</i>				
in recent 12 mo.	−0.122 (0.190)	0.167 (0.618)	−0.070 (0.171)	0.279 (0.594)
in yr prior 12 mo. ago	0.066 (0.181)	−0.355 (0.532)	−0.014 (0.165)	−0.390 (0.527)
<i>Mid-child life experience: # of mo. with disaster</i> (> 1000 days) & (< yr. before last yr.)				
	−0.035** (0.017)	−0.027 (0.017)	−0.024 (0.016)	−0.023 (0.017)
<i>Early-life experience: # of mo. with disaster</i> in the first 1000 days				
	−0.040*** (0.015)	−0.034** (0.015)	−0.031** (0.015)	−0.029** (0.014)
Female			−0.420*** (0.061)	−0.411*** (0.064)
Mother is alive			0.324** (0.160)	0.239 (0.159)
Father is alive			0.227** (0.105)	0.172 (0.112)
Mother is alive × living in same HH			0.057 (0.080)	0.157* (0.090)
Father is alive × living in same HH			−0.217*** (0.061)	−0.214*** (0.063)
Mother ever educated			1.340*** (0.082)	0.974*** (0.077)
Mother ever educated × has secondary education			0.996*** (0.067)	0.821*** (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 $t \times$ 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 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 (0.025)	−0.007 (0.026)
× Age 10–12	−0.015 (0.023)	−0.005 (0.023)
× Age 13–14	−0.017 (0.022)	−0.007 (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 (0.017)	0.008 (0.017)
× Age 13–14	−0.030 (0.022)	−0.027 (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 $t \times$ country FE	Y	Y

Note: This table shows heterogeneous analysis across ages of disaster effects on math-test scores. This corresponds to Equation 3 with interactions between disaster shocks and age groups. 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 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** (0.016)	−0.035** (0.017)
× Female	−0.014 (0.017)	−0.013 (0.017)
# of mo. with disaster in the first 1000 days		
× Male	−0.028 (0.017)	−0.029* (0.017)
× Female	−0.034** (0.015)	−0.030** (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 $t \times$ country FE	Y	Y

Note: This table shows heterogeneous analysis between genders of disaster effects on math-test scores. This corresponds to Equation 3 with interactions between disaster shocks and gender. 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 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.

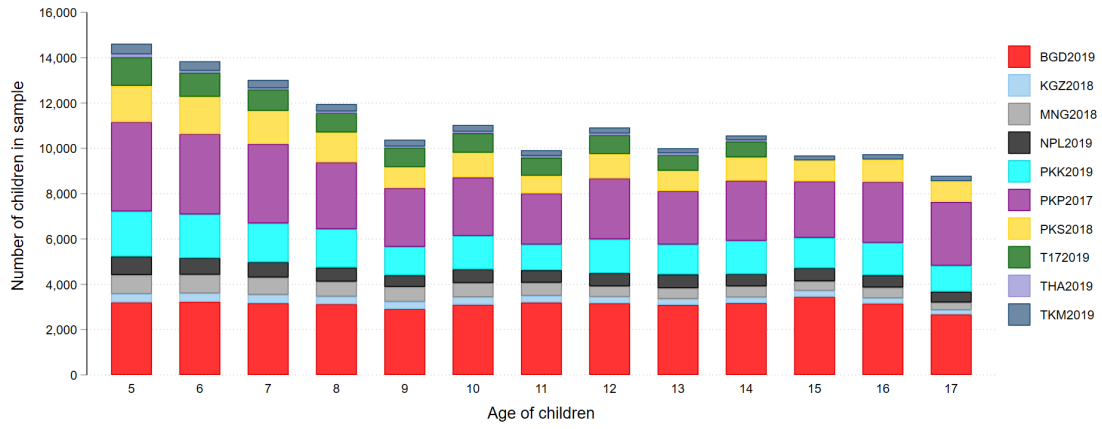
Table 11: Disasters and math-test scores, heterogeneity across gender and ages groups

	(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 (0.023)	−0.013 (0.023)
× Age 13–14	−0.026 (0.022)	−0.015 (0.022)
× Female		
× Age 7–9	−0.004 (0.026)	0.009 (0.027)
× Age 10–12	−0.006 (0.023)	0.003 (0.023)
× Age 13–14	−0.007 (0.022)	0.001 (0.022)
# of mo. with disaster in the first 1000 days		
× Male		
× Age 7–9	−0.036 (0.027)	−0.022 (0.026)
× Age 10–12	0.015 (0.021)	0.013 (0.020)
× Age 13–14	−0.018 (0.031)	−0.020 (0.033)
× Female		
× Age 7–9	−0.041** (0.021)	−0.022 (0.019)
× Age 10–12	0.012 (0.019)	0.001 (0.019)
× Age 13–14	−0.041* (0.024)	−0.034 (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

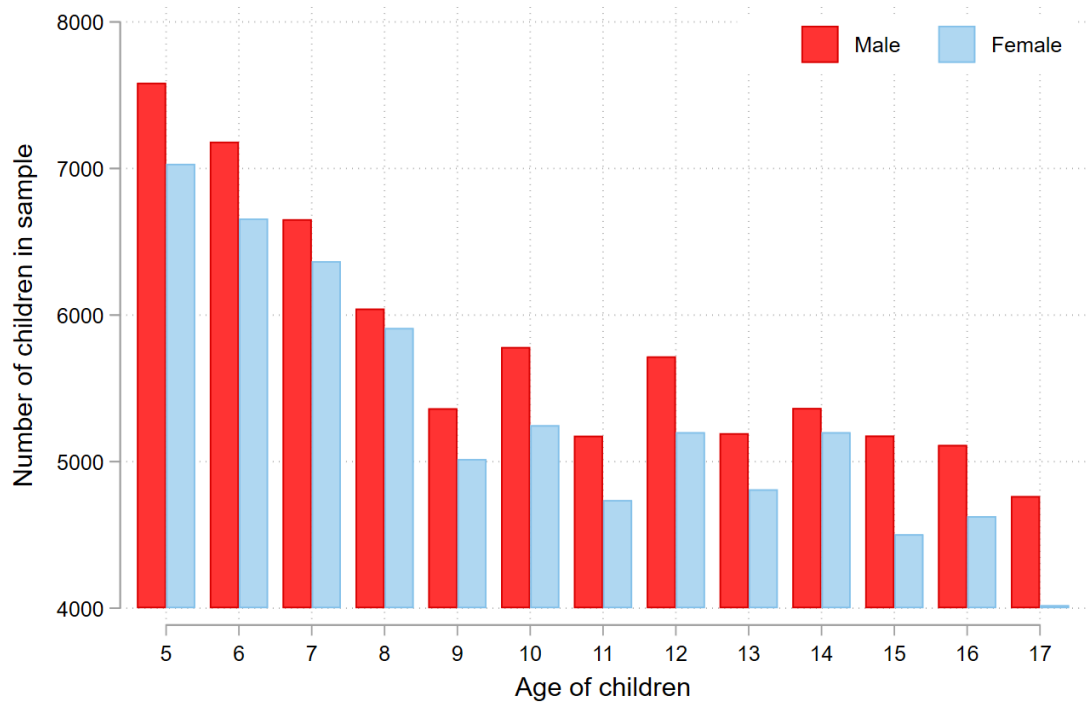
Note: This table shows heterogeneity analyses across gender and ages of disaster effects on math-test scores. This corresponds to Equation 3 with interacting disaster shocks between age groups and gender. The first 1000 days of life is defined as the period from conception to 24 months of age in child 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 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



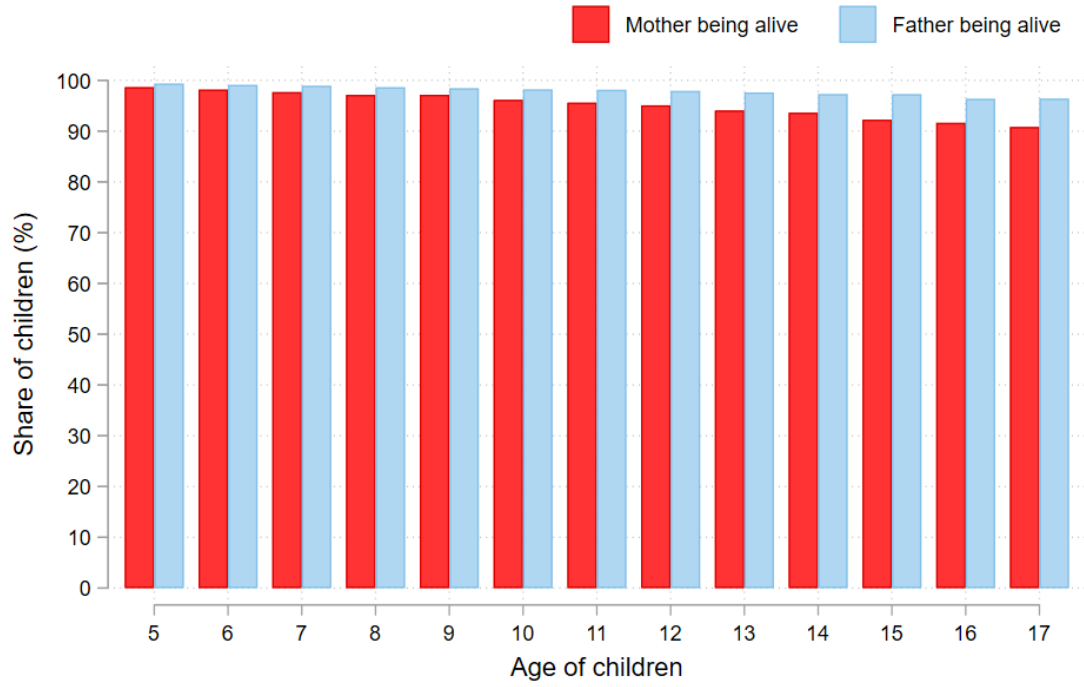
(b) Sample Size Across Gender and Ages



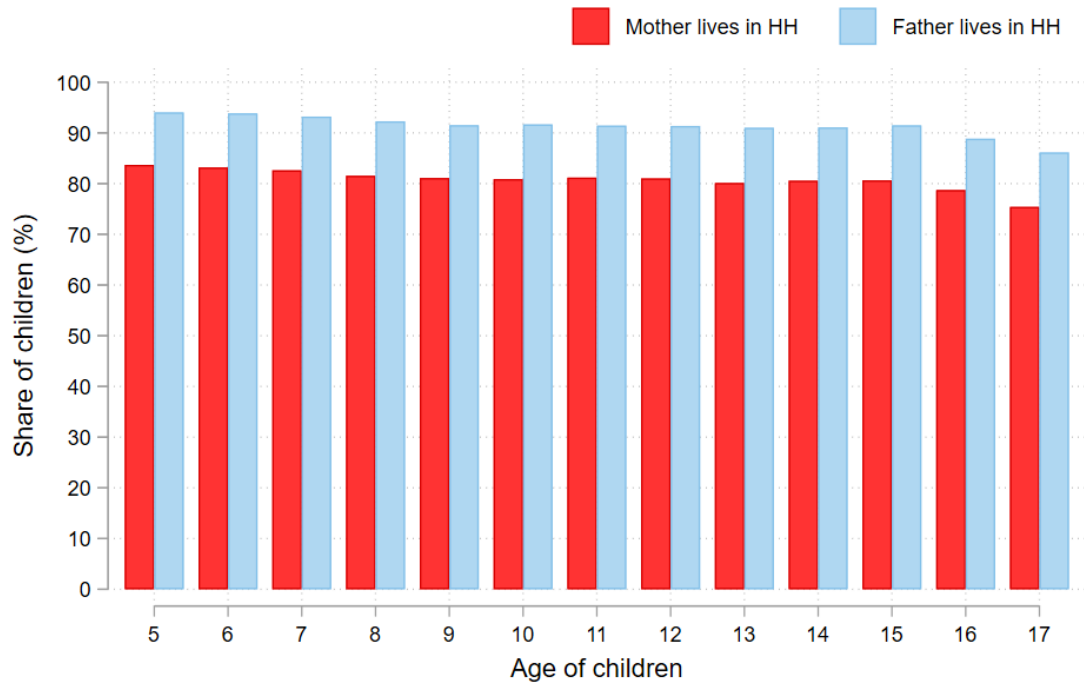
Note: Panel (a) shows number of children in each age and country. There are 144,471 children in full sample dominated by Bangladesh and Pakistan. For every age and country, there are more boys interviewed than girls. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan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



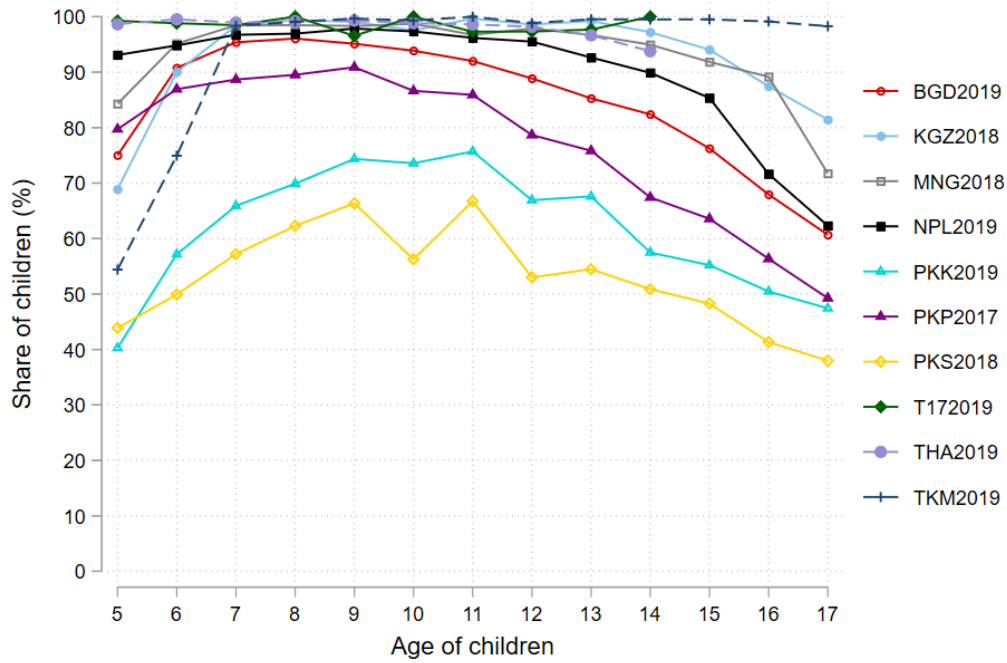
(b) Share of Parents Living with Mother or Father by Ages



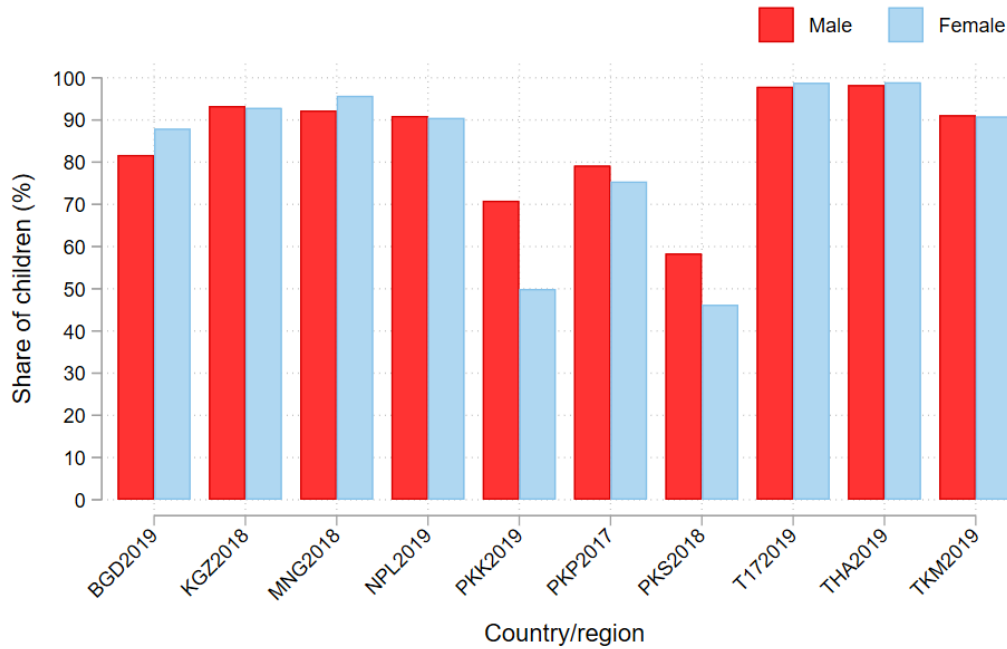
Note: Panel (a) shows the share of children with mother or father who is alive by child ages. Panel (b) shows the share of children living with either mother or father by ages. Blue (orange) bars represent shares of fathers (mothers).

Figure 3: Enrollment Fraction in Survey Year

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



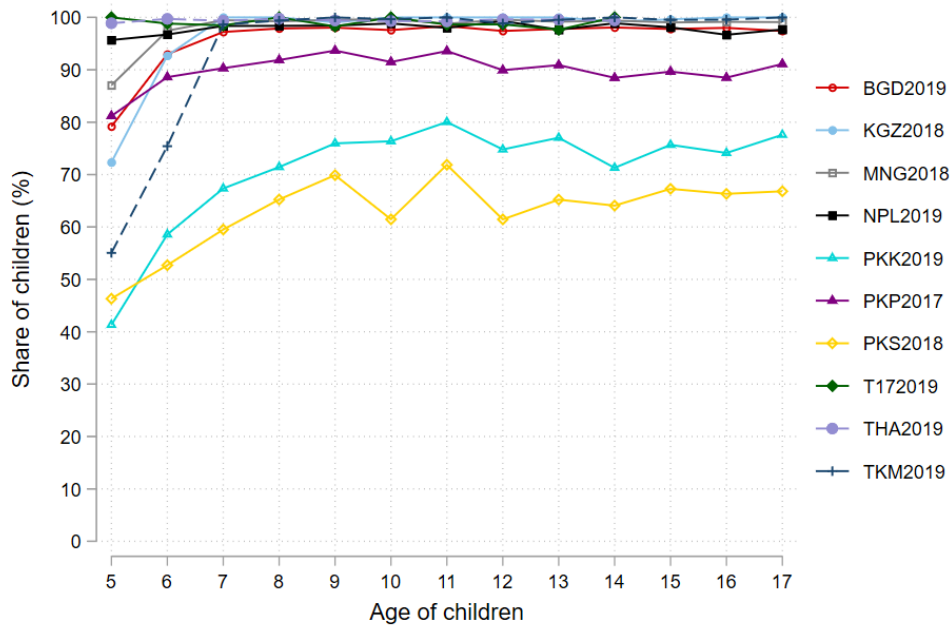
(b) Enrollment Fraction in Survey by Gender and Country



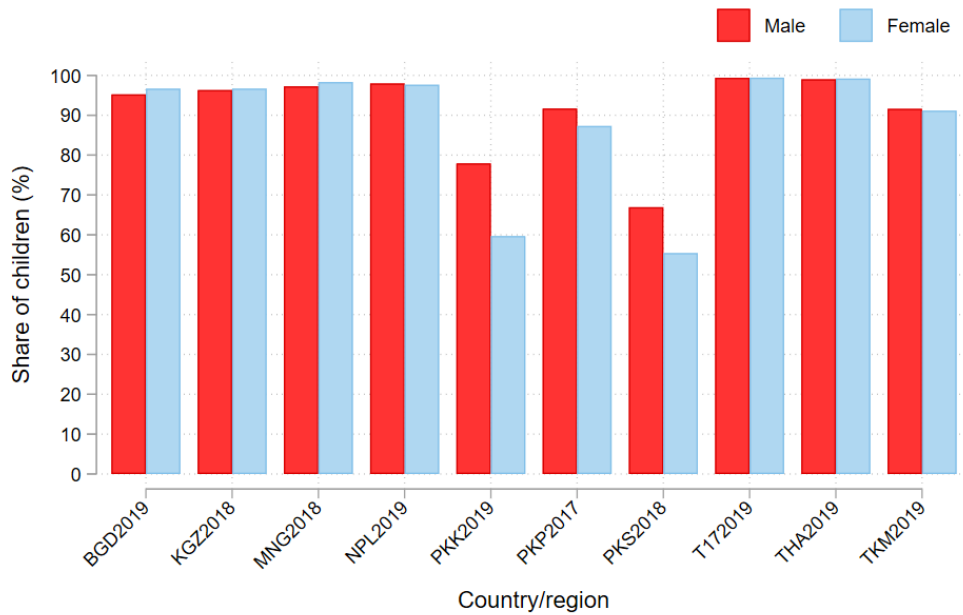
Note: Enrollment fraction in survey year. In Thailand, data are observed only up to age 14, in all other countries, data are available up to age 17. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS**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



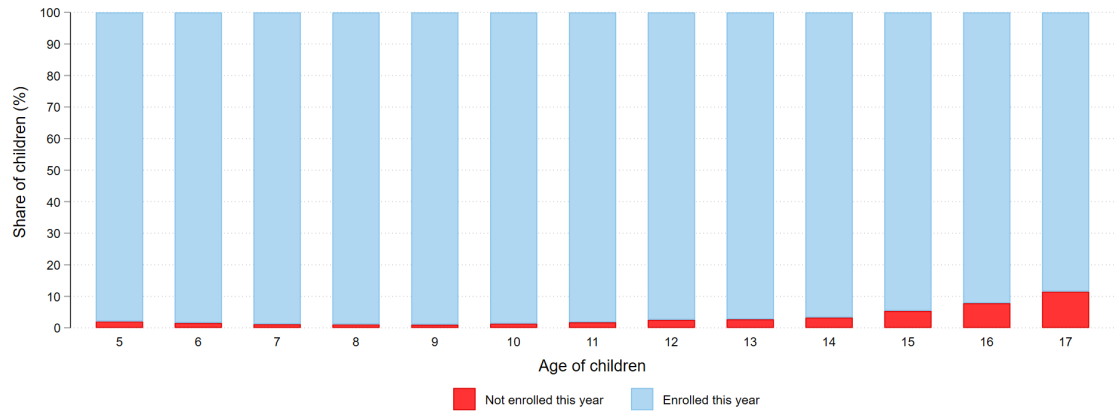
(b) Share of Children Ever Enrolled in School by Gender and Countries



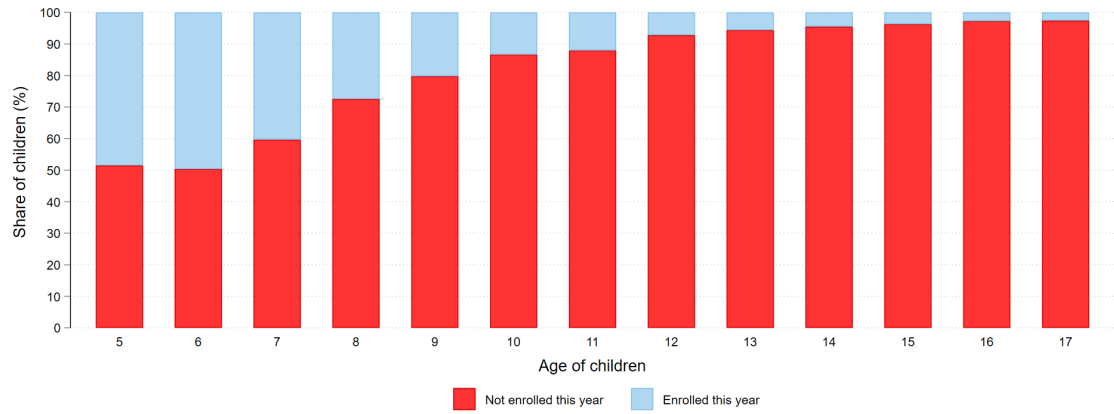
Note: The survey asks if a child has ever been enrolled in school. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017–2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged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

Figure 5: Enrollment Transition Probabilities By Ages

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



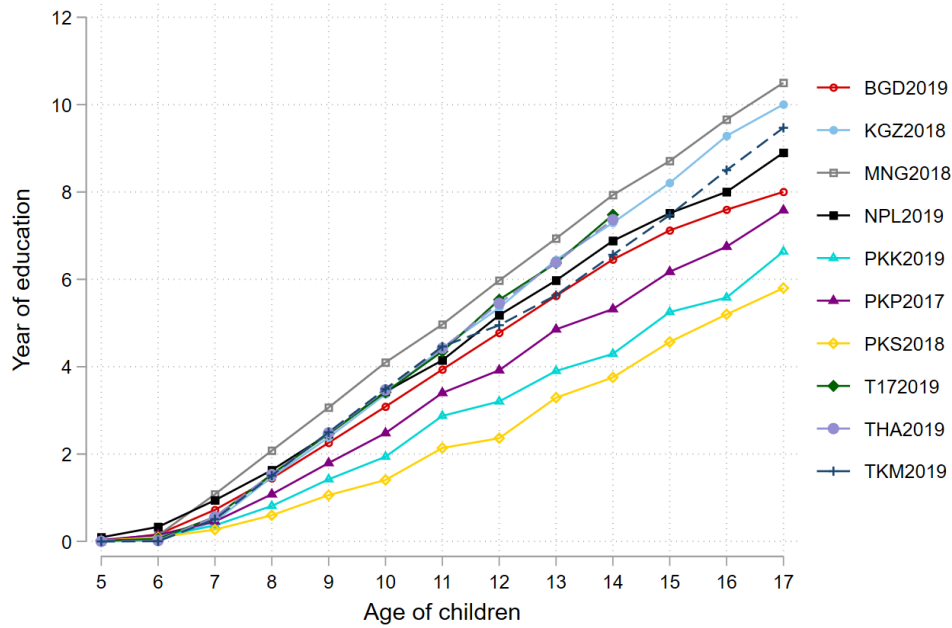
(b) Enrollment Fraction in Survey Year Conditional on Being **Enrolled** Previous Year



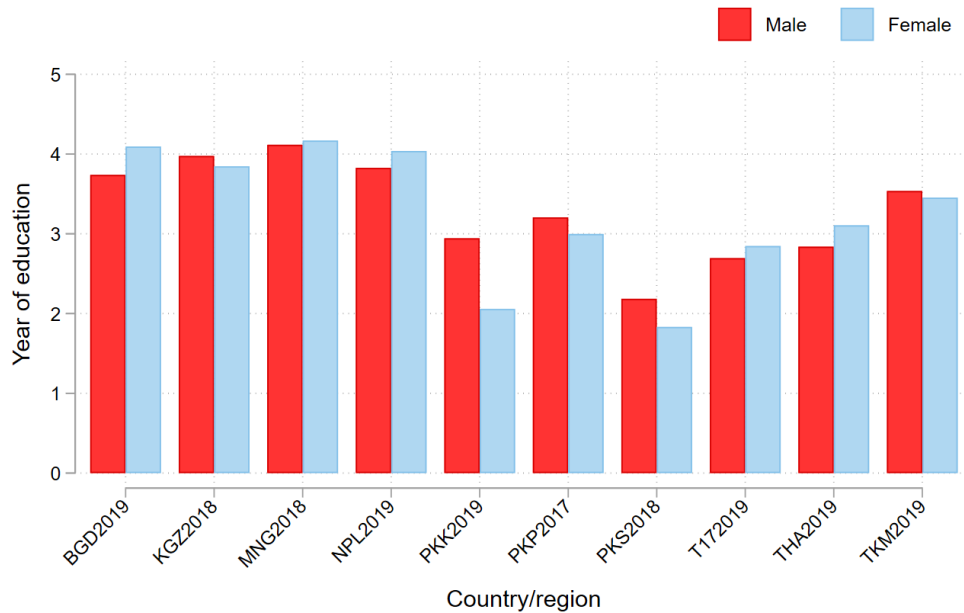
Note: Enrollment fraction in survey year conditional on being **Enrolled** previous year. The results show conditional probabilities.

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

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



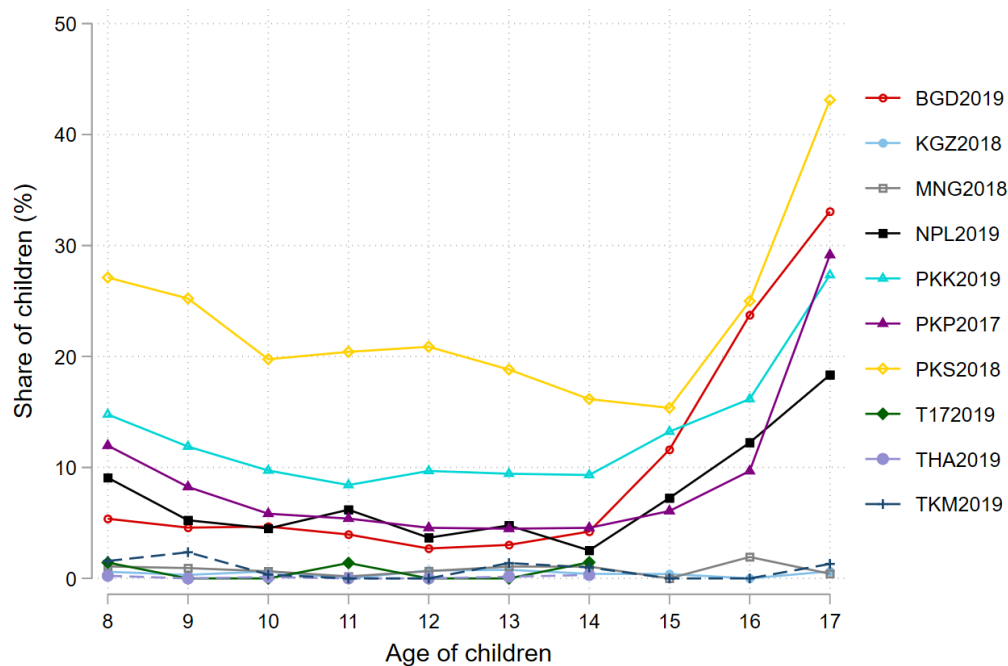
(b) Average Grades of Schooling Completed by Gender and Countries (All Available Ages)



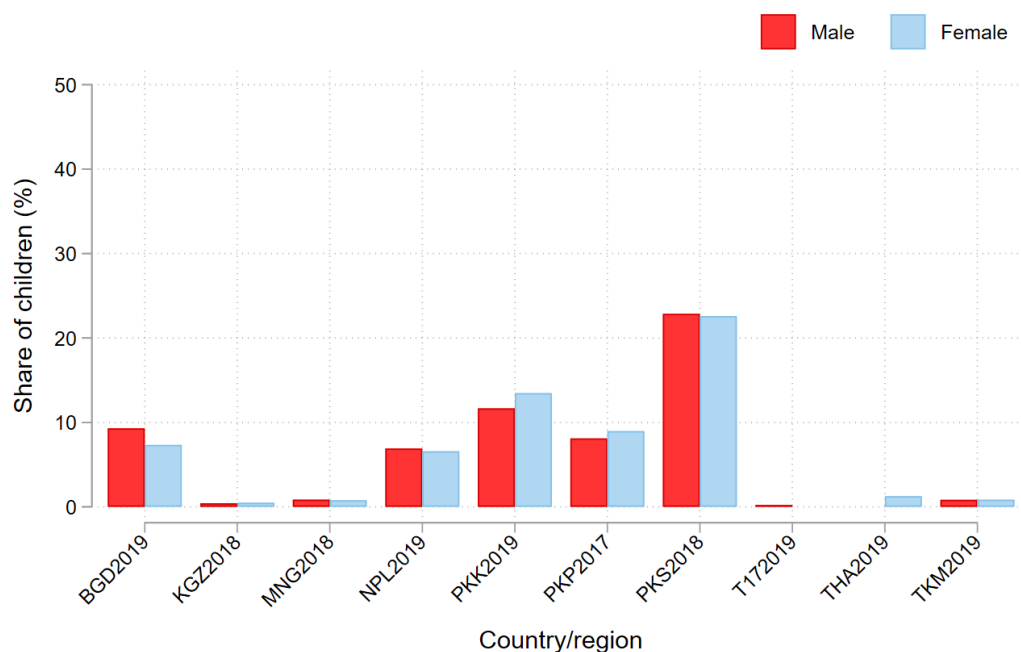
Note: In Thailand, data are observed only up to age 14, in all other countries, data are available up to age 17. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**),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



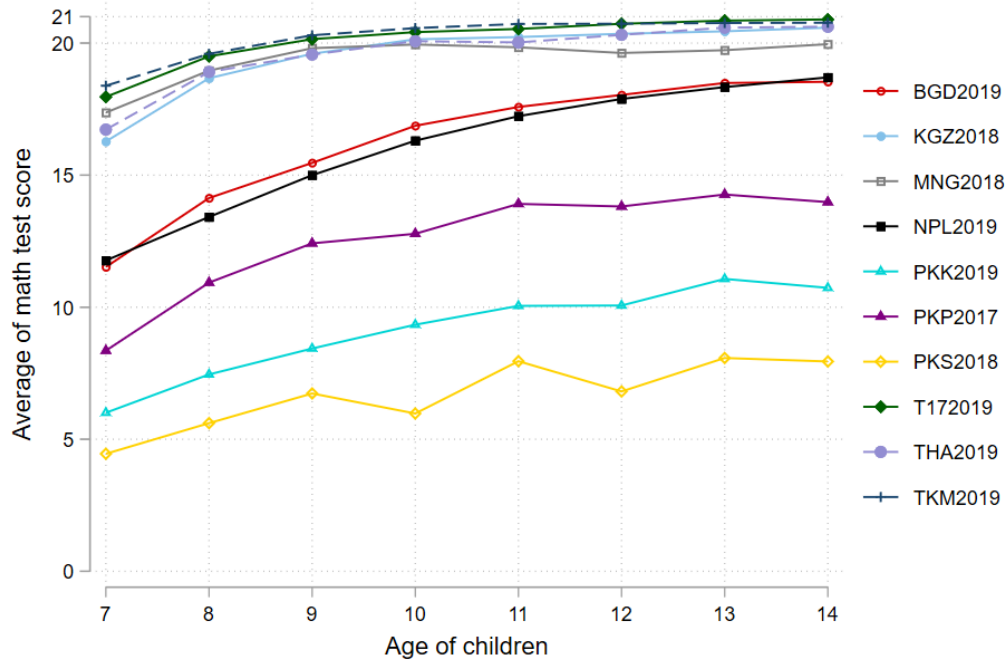
(b) Retention Rate by Gender and Countries (\geq Age 8)



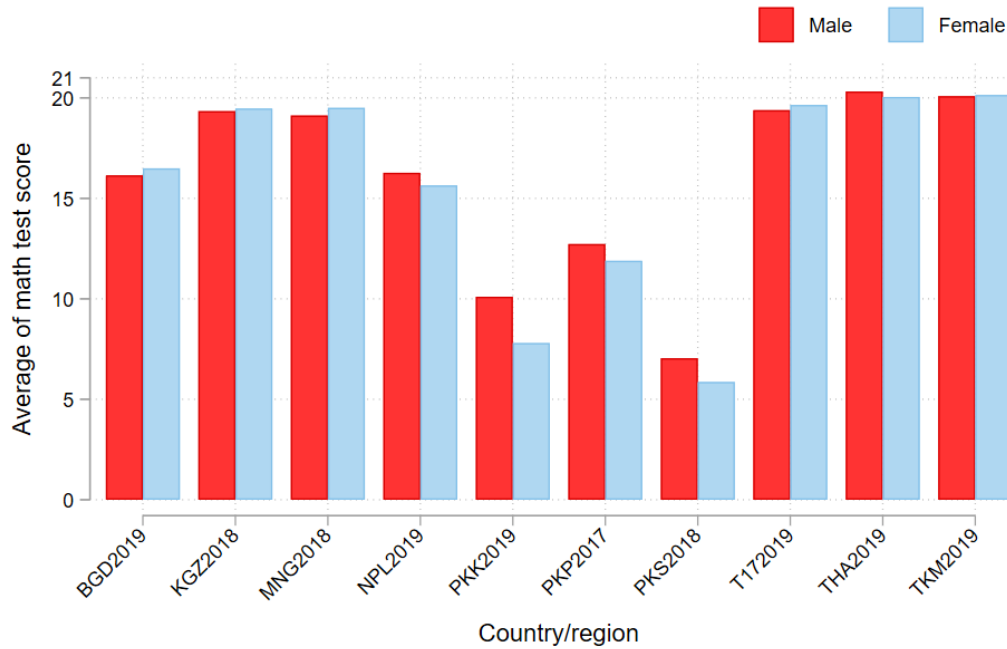
Note: If a child reports attending the same grade this and last year, a child is repeating a grade and experiencing grade retention. Gender indicator is 0 for male and 1 for female. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **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, **TKM**).

Figure 8: Distribution of Math-Test Scores

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

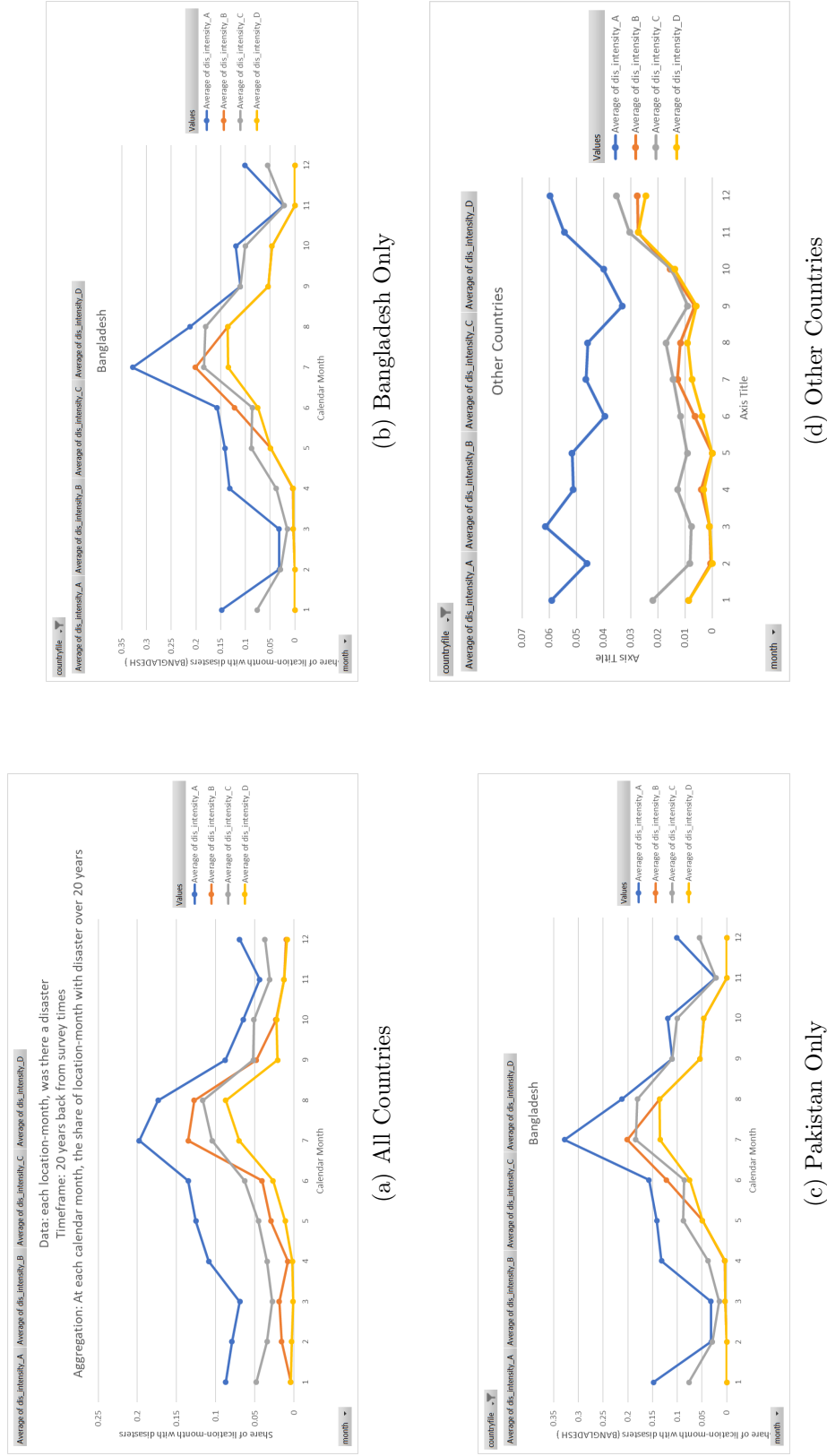


(b) Average of Math-Test Scores by Gender and Countries (Age 7-14)



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, **TKM**).

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



Note: For each location in every month from latest survey month to 20 years prior 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

Yujie Zhang, Jere R. Behrman, Emily Hannum, Minhaj Mahmud, and Fan Wang

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 Data Description

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). It provides internationally comparable data on the situation of children and women, offering key micro-level insights on progress in human capital development globally. Between the mid-1990s and 2022, MICS has conducted multiple rounds of surveys covering 118 countries. MICS data is publicly available datasets can be downloaded from <https://mics.unicef.org/surveys> in .sav format.

MICS surveys are cross-sectional and use multistage probability designs. It is representative at national and sub-national levels. In each round, MICS provides nearly uniform data collection instructions and survey questions across survey countries. The household as well as individual questionnaires 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 one randomly selected child age 5-17 in each household.

We focus on MICS6 because it includes questions on whether a child experienced school closure due to natural disasters for children age 5 to 17. 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 do not consider previous rounds because although children age 5 to 17 data were collected using the household questionnaire, including education, child labor, and child discipline modules, the particular information on school closure and teacher truancy is not collected, which is essentially our measure for education system resilience.

Geographically, within all Asian countries covered in MICS6, we focus on low- and middle-income countries whose data is collected pre-pandemic. This includes 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}.

Although we choose the countries mainly because of the availability of data in MICS6, this is not the only reason. For some countries, the stakes in terms of negative impacts are particularly high even they are hit by disasters at same severity level. For example, Bangladesh

A.1. For example, MICS6 for Viet Nam started in 2020 until 2021, and excluded in this project

is a densely populated, low-lying country with substantial exposure to cyclones, floods and drought and is predicted to be affected by increasingly severe 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 window, sample size, and summary statistics for some key variables.

A.2 Measures: Educational Outcomes

The educational outcomes will be the grade progression, school enrollment and the foundational learning skills for children age 7 to 14. The MICS6 records the highest level and grade or year of school the child has ever attended and if the child attended school or any early childhood education program in current school year. We show the average enrollment rate at region level^{A.2} for each countries in Table 1. In addition, MICS6 offers critical resource to measure and monitor progress towards Sustainable Development Goal (SDG) 4 (Mizunoya and Amaro 2020). Learning skill on literacy and numeracy are assessed for children aged 7 to 14 years old by the interviewer, hence our analysis is not subject to selection bias due to school enrollment or attendance.

The key educational outcomes including enrollment, attainment, progression, and retention are obtained from both household questionnaire and children age 5-17 questionnaire. However, test score only shows in children age 5-17 questionnaire. If the respondent in children 5-17 questionnaire is the same as in household questionnaire, then the below questions are skipped in children 5-17 questionnaire. Every question starting with “CB” are form children 5-17 survey questionnaire while “ED” denotes those in household questionnaire. The first step for variable construction is replacing the missing value in CB questions with those recorded in ED ones. Then, we only use CB variables to construct measures.

The questions providing educational outcomes information include:

- 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?

A.2. The definition of region differs across countries. It is district for Bangladesh, oblast for Kyrgyzstan, district for Pakistan, provinces for Thailand, respectively, and region for other countries.

- 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?

A.2.1 Enrollment Path

We are able to categorize all children in the sample into five paths considering the enrollment status ever, enrollment status in last school year, and enrollment status in this school year:

- On path A, children should have attended some education level. They should have been "ever enrolled", and both enrolled in last year and this year.
- On path B, children have been "ever enrolled", enrolled in last year but not enrolled this year.
- On path C, children have been "ever enrolled", not enrolled in last year yet enrolled this year.
- On path D, children have been "ever enrolled", not enrolled in last year and also not enrolled this year. On path E, children have never been enrolled to any program.

In the design of survey, if one child answered "No" to CB4 or have missing value for CB4, which means she has never been enrolled in any education program, should skip the following questions CB5-CB10. However, in our sample, there are some (but very few) children who has answer "No" to CB4, but also have information on CB7 or CB9.

First, we construct variable *edu_everschool* from CB4 but replace "do not know" or "no response" as missing value. From CB7, we construct *edu_enrolthisy* with the same logic as well as *edu_enrollasty* from CB9 question.

There are 144,471 children in whole sample. In 18,020 children who answer "never enrolled in any school", there are 47 children are "enrolled in last school year". Also, 60 children are "never enrolled in any school", but are "enrolled in this school year". More specifically, we check the value of *edu_enrollasty* and *edu_enrolthisy* for all children who have "No" or missing value for *edu_everschool*. 43 children have answer "No" to "ever enrolled or not", but "Yes" to both enrollment in last and this year. 4 children have answer "No" to "ever enrolled or not", but *edu_enrollasty* = 1 and *edu_enrolthisy* = 0. 17 children have value as *edu_everschool* = 0, *edu_enrollasty* = 0, and *edu_enrolthisy* = 1. 50 children have value as *edu_everschool* = 0, *edu_enrollasty* = 0, and *edu_enrolthisy* = 0. 1 child have value as *edu_everschool* = 0, *edu_enrollasty* with missing value, and *edu_enrolthisy* = 0. Another 1 child has value as *edu_everschool* = 0, *edu_enrollasty* = 0, and *edu_enrolthisy* with missing value.

9 children have missing value for *edu_everschool*, *edu_enrollasty* = 1, and *edu_enrolthisy* = 1. No children have missing value for *edu_everschool*, *edu_enrollasty* = 1, and *edu_enrolthisy* = 0. 2 children have missing value for *edu_everschool*, *edu_enrollasty* = 0, and *edu_enrolthisy* = 1. 1 children have missing value for *edu_everschool*, *edu_enrollasty* = 0, and *edu_enrolthisy* = 0.

In total, there are 128 children who should have skipped question CB7 and CB9 but did not. Among them, 75 children answer "Yes" to either enrollment question of last year or this year. We construct the new ever enrollment variable E_{ever} as equal to $edu_everschool$ and move these 75 children out of path E - never enrolled. As a result, there are 17,956 children who are never enrolled in any program, with 45 missing value.

Enrollment status for last school year E_{t-1} is then constructed from $edu_enrolllasty$ and replace missing value with zero if $E_{ever} = 0$. 37,095 children are not enrolled in last school year with 77 missing information.

Enrollment status for this school year E_t is constructed from $edu_enrollthisy$ and replace missing value with zero if $E_{ever} = 0$. 31,021 children are not enrolled in this school year with 61 missing information.

The next step is building path for each children and based on E_{ever} , E_{t-1} and E_t and eventually there are 104,196 children on path A, 3,099 children on path B, 9,178 on C, 8,852 on D, and 17,956 on path E. Only 90 children are not categorized into any path.

A.2.2 Grade and Attainment

It is straightforward to obtain education level and grade of last school year and this school year from CB8 and CB10, respectively. CB5 shows the highest level and grade the child has ever attended. In MICS raw data, there are two variables assigned to each question, showing separately level and grade in that level. Since education system differs across countries, we construct uniform "year of education" variable to denote the grade one child was or is enrolled for highest grade, last year, and this year: $edu_yoe_highest$, edu_yoe_lasty , and edu_yoe_thisy .

For path A, it should be the case that grade calculate from CB5 should be equal to "grade in this year" from CB8. It turns out 103,495 out of 104,196 children have same information for both variables. Similarly, we check this for children on path C, as they are also enrolled in this year although they did not enroll in last year. 9,061 out of 9,178 children have matched information. Then for path B, there should be that highest grade from CB5 equal to that calculated from CB10, because children are enrolled last year but not this year, so the highest grade she has ever attended should be the one she went last year. 2,451 out of 3,097 children satisfy this assumption.

Eventually, we have $G_{t-1} = edu_yoe_lasty$ for path A and B, $G_t = edu_yoe_thisy$ for A and C.

There are 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 . We first construct the variable showing if each grade is completed directly from CB6 question. This $edu_complete$ is an indicator being 1 if the child answers "Yes" to CB6, 0 if "No", and missing if "No response" or "do not know".

For path A, highest attainment is the same as grade in this year (edu_yoe_thisy) if $edu_complete$ is 1. It is edu_yoe_thisy minus 1 if $edu_complete$ is not 1. For path B, highest attainment is calculated similarly as in path A but use grade in last year (edu_yoe_lasty). Path D is treated identical as path A. Path D is where we indeed use the highest grade ($edu_yoe_highest$) and attainment is equal to $edu_yoe_highest$ if $edu_complete$ is 1, $edu_yoe_highest$ minus 1 other-

wise. For path E, the highest attainment is assigned as zero.

Attainment at start of last school year A_{t-1} is grade enrolled in last year minus 1 for both path A and B. For path C, since the child is not enrolled in last year but enrolled in this year, we know the attainment at start of last year should be the grade in this year minus one. Children on path D and E have $A_{t-1} = A_{max}$.

Attainment at start of this school year A_t is grade enrolled in 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 grade in this year minus one. Children on path D and E have $A_{t-1} = A_{max}$.

A.2.3 Retention

We construct binary variable R_t to capture the retention in this school year of each child. As retention is defined as repeating the grade you attended last year in this school year, only children who are enrolled both years have information on this (path A). It is one if $G_t = G_{t-1}$ and zero otherwise.

A.2.4 Test Score

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: School Shutdown and Teacher Truancy

MICS6 surveys if in the last year, the children's school has been closed on a school day due to the following reasons: natural disasters (flood, cyclone, epidemics or similar), man-made disasters (fire, building collapse, riots or similar), and teacher strike. Additionally, they ask if the child was unable to attend class due to teacher absenteeism. Although it is not explicit on the reason why teachers are absent, we cannot rule out the possibilities that teachers cannot work due to natural disasters. We will use these two dimensions, school shutdown and instructor truancy, to reveal the education system resilience through which natural disaster affects educational outcomes. In Table 1, we first aggregate the reported answers at the region level to generate the rate of reporting schools closed due to natural disaster. The rate varies largely within countries. For example, Lalmonirhat district has the highest rate of school closure in Bangladesh, 54.4%, where 204 children experienced school closure and 171 did not, while the rate is lower than 2% in several other districts. The range for Thailand is also as large as 50 percentage points. The same methodology is applied to the rate of teacher absenteeism question. This also varies across locations, which is 26.33% for Joypurhat and zero for Habiganj district in Bangladesh, respectively. Then for each country, the average and standard deviation of both rates are calculated.

Below questions from children 5-17 questionnaire are used to generate two measures.

PR12. In the last 12 months, has (name)'s school been closed on a school day due to any of the following reasons: [A] Natural disasters, such as flood, cyclone, epidemics or similar? [B] Man-made disasters, such as fire, building collapse, riots or similar? [C] Teacher strike? [X] Other?

PR13. In the last 12 months, was (name) unable to attend class due to (his/her) teacher being absent?

It is trivial to know if there was school closure due to natural disaster directly from PR12A. We treat do not know as missing and generate indicator, sch_close_nat equals 1 if the child has experienced school closure due to natural disaster.

For teacher truancy, we consider PR12C and PR13 answers. Although PR12 answer C only refers to teacher strike in the questionnaire, the label for this variable in raw data from MICS shows "have your school closed due to teacher strike/teacher being absent". It is understandable that the respondent may not know exactly why teacher is absent and if it is due to teacher strike, so they record the answer without distinguishing both. As a result, PR12C and PR13 both imply if the child's learning process has been interrupted ever due to teacher truancy in last 12 months.

PR12C answer does not exist for all countries. For those that do not have raw variable PR12C, indicator *sch_tea_abs* is constructed from only PR13. It is 1 if the child answers Yes to PR13 and 0 if answer is No. For those that have information of PR12C and PR13 both, we first construct indicator *sch_close_tea_raw* from PR12C, being 1 if in last 12 months there was school closed due to teacher strike or absent. Then another indicator *not_attend_tea_raw* is generated from PR13 being 1 if the child was unable to attend class due to teacher absent. If either of these two indicators is one, then we treat this child as "having experienced teacher truancy". If both indicators are zero, then we confirm the child's study in last year has not been interrupted due to teacher truancy. Indicator *sch_tea_abs* is used to capture this.

Like in construction for key educational outcomes, we check if there is misreporting issue behind our two organizational factor measures. Question PR12 and PR13 are not asked for children who are in age 5-6 or 15-17 years. Then, they should be skipped and have missing value if the child is not enrolled in this school year.

By tabulating age and enrollment status in this year E_t with *sch_close_nat* and *sch_tea_abs*, we notice there is only one child that has not enrolled this year, but information on school closure and teacher truancy. The child has $E_t = 0$, but *sch_close_nat* = 0 and *sch_tea_abs* = 0. For children who are not in age 7-14, only 2 children are observed as not have experienced school closure due to natural disaster and enrolled this year, while 1 child is observed as not have teacher truancy and enrolled this year. All other children who are not age 7-14, no matter they are enrolled this year or not or the enrollment status this year is missing, the *sch_close_nat* and *sch_tea_abs* are missing.

For children who are 7-14 years old, 74,207 are enrolled in this year. 87.43% of them reported not have experienced school closure due to natural disaster, while 8.59% have, which is 6,372 children in our whole sample (3.98% are missing). Additionally, 7,667 children reported having experienced teacher truancy (10.33%) and 6.39% are missing.

A.4 Measures: Child attributes

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.5 Measures: Parental and Household background

A.5.1 Parent 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.5.2 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 elsewhere. Based on these information, we construct indicators of maternal, paternal, and joint parental loss and parental-child co-residence status. Figure 2 present distributions of parental loss and parental-child co-residence status.

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) with comprehensive information on disasters which led to the substantial loss of human life including natural disasters and technological disasters. Occurrence and effects of more than 21,000 disasters worldwide 1900-present are recorded to support decision making for disaster preparedness, vulnerability assessment, and prioritize resource allocation for disaster response. EM-DAT is compiled from various sources: UN agencies, non-governmental organisations, insurance companies, research institutes, and press agencies. To ensure the quality of data, reliability score is assigned from one to five with higher number showing higher quality.

EM-DAT data documents all the natural disasters as a group and as five subgroups—geophysical, meteorological, hydrological, climatological, and biological. One or more specific natural disasters are recorded in each subgroups, while technological disasters include various types of industrial accidents, miscellaneous accidents, and transport accidents (Mavhura and Aryal 2023; Guha-Sapir, Below, and Hoyois). Disasters are included in the EM-DAT/CRED database if it satisfies any of the following 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 are internationally standardized and allows linkage to other databases.

Conditional on disaster type, countries of occurrences, and time periods of occurrences, the raw data can be downloaded as an Excel Worksheet. In this raw file, each row is one disaster and columns record information associated with each disaster. One disaster has one unique disaster identifier generated by year, sequence number, and country ISO alpha 3 code. Each disaster has same identifier and when one disaster affects several countries, it is recorded several times. For example, "2016-0375-PAK" is the identifier to a flash flood that happened in Pakistan in 2016.

The information of each disaster can be categorized into two groups: context variables and impact variables.

Geographical and temporal information of each disaster are provided in context variables such as country name, ISO Code, region, continent, and river basin. Location of epicenter of earthquake is provided for earthquake. Admin level code and location names of all locations affected by each disaster are also listed, which are the crucial variables to use in this project to link individuals' location. Temporal information includes start date, end date, and local time. There is also physical characteristics such as origin, associated disasters 1 and 2, disaster magnitude scale and value. Aid contribution, OFDA response, appeal for international assistance and declaration are offered as disaster status. Impact variables enable us to 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 the disaster. Total estimated damages, reconstruction cost and insured losses are additionally included as economic impact information. Using "2016-0375-PAK" as an example, from variable "Origin",

we know this flash flood is resulted from heavy rain. This flood started on August 5, 2016, and ended August 8, 2016. Although it only last 3 days, 32 people were dead and 2,900 people were homeless due to this disaster. In variable "Location", "Balochistan, Sindh provinces" as listed. The variable "GeoLocations" also records the location names that had been affected, and it shows "Balochistan, Sindh (Adm1)". In this example, the "GeoLocations" variable information matches that in "Location", but it is not always the case. These are crucial variables we use to link EM-DAT disaster with children in MICS, and we discuss the linkage strategy in the following section.

B.2 Combining the EM-DAT dataset with MICS data

C Additional Figures and Tables (online)

This section provides additional tables and figures.

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

	5th	Percentiles		20th	Mean	SD	Obs
	10th	15th					
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 (0.005)	0.003 (0.005)	-0.004 (0.006)	0.003 (0.003)
# of mo. with disaster in the first 1000 days	-0.001** (0.000)	-0.001** (0.000)	-0.001** (0.000)	-0.001** (0.000)
Enrollment in year $t - 1$	0.388*** (0.012)	0.388*** (0.012)	0.388*** (0.012)	0.388*** (0.012)
Attainment at start of t	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)
Female	-0.006*** (0.002)	-0.006*** (0.002)	-0.006*** (0.002)	-0.006*** (0.002)
Mother is alive	-0.009 (0.006)	-0.009 (0.006)	-0.009 (0.006)	-0.009 (0.006)
Father is alive	0.012*** (0.004)	0.012*** (0.004)	0.012*** (0.004)	0.012*** (0.004)
Mother is alive \times living in same HH	0.025*** (0.005)	0.025*** (0.005)	0.025*** (0.005)	0.025*** (0.005)
Father is alive \times living in same HH	-0.005** (0.002)	-0.005** (0.002)	-0.005** (0.002)	-0.005** (0.002)
Mother ever educated	0.041*** (0.003)	0.041*** (0.003)	0.041*** (0.003)	0.041*** (0.003)
Mother ever educated \times has secondary education	0.011*** (0.002)	0.011*** (0.002)	0.011*** (0.002)	0.011*** (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* (0.056)	0.040 (0.084)
× Age 9–12	−0.110** (0.055)	0.034 (0.084)
× Age 13–17	−0.101* (0.058)	0.044 (0.086)
× Bangladesh		
× Age 5–8	0.044*** (0.014)	0.297*** (0.106)
× Age 9–12	−0.011 (0.008)	0.240** (0.109)
× Age 13–17	−0.027** (0.012)	0.223** (0.111)
× Other countries		
× Age 5–8	−0.005 (0.008)	0.039* (0.020)
× Age 9–12	−0.013* (0.007)	0.031 (0.020)
× Age 13–17	−0.013 (0.010)	0.033 (0.022)
# of mo. with disaster in the first 1000 days		
× Pakistan		
× Age 5–8	−0.006** (0.003)	−0.006** (0.003)
× Age 9–12	−0.001 (0.001)	−0.001 (0.001)
× Age 13–17	−0.001 (0.002)	−0.001 (0.002)
× Bangladesh		
× Age 5–8	0.003 (0.002)	0.003 (0.002)
× Age 9–12	−0.002** (0.001)	−0.002* (0.001)
× Age 13–17	−0.003*** (0.001)	−0.003*** (0.001)
× Other countries		
× Age 5–8	0.002*** (0.000)	0.002*** (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.		
× Male	−0.003 (0.006)	0.056** (0.025)
× Female	−0.005 (0.006)	0.056** (0.025)
# of mo. with disaster in the first 1000 days		
× Male	−0.002*** (0.001)	−0.002*** (0.001)
× Female	−0.000 (0.000)	−0.000 (0.000)
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 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 (0.171)	0.055 (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 (0.146)	0.164 (0.135)
# of mo. with disaster in mid-child life		-0.022 (0.017)	-0.022 (0.017)
# of mo. with disaster in the first 1000 days		-0.029** (0.015)	-0.030** (0.015)
Female	-0.417*** (0.060)	-0.419*** (0.061)	-0.419*** (0.061)
Mother is alive	0.327** (0.160)	0.325** (0.160)	0.324** (0.160)
Father is alive	0.223** (0.105)	0.225** (0.105)	0.225** (0.105)
Mother is alive \times living in same HH	0.053 (0.080)	0.055 (0.080)	0.056 (0.080)
Father is alive \times living in same HH	-0.215*** (0.061)	-0.215*** (0.061)	-0.216*** (0.061)
Mother ever educated	1.341*** (0.082)	1.340*** (0.082)	1.340*** (0.082)
Mother ever educated \times has secondary education	0.998*** (0.067)	0.996*** (0.067)	0.996*** (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 \times 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 (0.023)	−0.008 (0.022)
× Bangladesh	−0.054** (0.024)	−0.061** (0.025)
× Others	0.034 (0.027)	0.033 (0.028)
# of mo. with disaster in the first 1000 days		
× Pakistan	−0.093*** (0.020)	−0.076*** (0.020)
× Bangladesh	0.025 (0.031)	0.019 (0.031)
× Others	0.033 (0.030)	0.046 (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 $t \times$ 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 (0.070)	0.015 (0.073)
× Age 10–12	−0.124** (0.050)	−0.092** (0.044)
× Age 13–14	−0.054 (0.037)	−0.050 (0.033)
× Bangladesh		
× Age 7–9	−0.153*** (0.057)	−0.128** (0.060)
× Age 10–12	−0.030 (0.030)	−0.020 (0.031)
× Age 13–14	−0.065** (0.029)	−0.069** (0.030)
× Other countries		
× Age 7–9	0.031 (0.042)	0.052 (0.044)
× Age 10–12	0.032 (0.040)	0.048 (0.040)
× Age 13–14	0.032 (0.042)	0.048 (0.042)
# of mo. with disaster in the first 1000 days		
× Pakistan		
× Age 7–9	−0.198*** (0.065)	−0.124** (0.060)
× Age 10–12	−0.013 (0.024)	0.005 (0.024)
× Age 13–14	−0.090 (0.056)	−0.069 (0.060)
× Bangladesh		
× Age 7–9	0.075 (0.057)	0.086 (0.059)
× Age 10–12	0.038 (0.032)	0.006 (0.033)
× Age 13–14	−0.012 (0.031)	−0.002 (0.033)
× Other countries		
× Age 7–9	0.017 (0.029)	0.027 (0.029)
× Age 10–12	0.040 (0.034)	0.028 (0.032)
× Age 13–14	0.086*** (0.032)	0.061* (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** (0.005)	0.003 (0.008)	0.002 (0.006)
# of mo. with disaster in the first 1000 days	-0.002*** (0.001)	-0.002*** (0.001)	-0.004*** (0.001)
Enrollment in year $t - 1$	0.386*** (0.012)	0.387*** (0.012)	0.385*** (0.012)
Attainment at start of t	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)
Female	-0.006*** (0.002)	-0.006*** (0.002)	-0.006*** (0.002)
Mother is alive	-0.009 (0.006)	-0.009 (0.006)	-0.009 (0.006)
Father is alive	0.012*** (0.004)	0.012*** (0.004)	0.012*** (0.004)
Mother is alive \times living in same HH	0.025*** (0.005)	0.025*** (0.005)	0.025*** (0.005)
Father is alive \times living in same HH	-0.005** (0.002)	-0.005** (0.002)	-0.005** (0.002)
Mother ever educated	0.041*** (0.003)	0.041*** (0.003)	0.041*** (0.003)
Mother ever educated \times has secondary education	0.011*** (0.002)	0.011*** (0.002)	0.011*** (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 $t - 1 \times$ age group FE	Y	Y	Y
Attainment $t \times$ age group FE	Y	Y	Y
Enrollment $t - 1 \times$ country FE	Y	Y	Y
Attainment $t \times$ 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** (0.009)	0.019* (0.011)	0.045*** (0.008)
× Age 9–12	−0.014** (0.007)	−0.004 (0.008)	−0.017*** (0.006)
× Age 13–17	−0.003 (0.009)	−0.008 (0.010)	−0.025*** (0.008)
# of mo. with disaster in the first 1000 days			
× Age 5–8	−0.001 (0.003)	−0.001 (0.001)	−0.005* (0.003)
× Age 9–12	−0.003*** (0.001)	−0.002*** (0.001)	−0.003*** (0.001)
× Age 13–17	−0.002*** (0.001)	−0.003*** (0.001)	−0.003*** (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** (0.009)	0.015 (0.011)	0.036*** (0.009)
× Age 9–12	−0.022*** (0.007)	−0.014 (0.009)	−0.031*** (0.007)
× Age 13–17	−0.011 (0.009)	−0.016 (0.010)	−0.036*** (0.008)
× Female			
× Age 5–8	−0.019* (0.010)	0.022* (0.012)	0.053*** (0.008)
× Age 9–12	−0.005 (0.007)	0.007 (0.009)	−0.001 (0.006)
× Age 13–17	0.005 (0.009)	0.003 (0.010)	−0.011 (0.008)
# of mo. with disaster in the first 1000 days			
× Male			
× Age 5–8	0.002 (0.003)	0.001 (0.002)	−0.001 (0.003)
× Age 9–12	−0.003*** (0.001)	−0.003*** (0.001)	−0.004*** (0.001)
× Age 13–17	−0.002** (0.001)	−0.004*** (0.001)	−0.003** (0.001)
× Female			
× Age 5–8	−0.005* (0.003)	−0.002 (0.002)	−0.009*** (0.003)
× Age 9–12	−0.003*** (0.001)	−0.000 (0.001)	−0.002* (0.001)
× Age 13–17	−0.002** (0.001)	−0.003** (0.001)	−0.003** (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
<i>Recent experience: had disaster</i>			
in recent 12 mo.	−0.364 (0.275)	−0.015 (0.209)	−0.380 (0.314)
in yr prior 12 mo. ago	0.016 (0.254)	0.213 (0.204)	−0.058 (0.188)
<i>Mid-child life experience: # of mo. with disaster (> 1000 days) & (< yr. before last yr.)</i>			
	−0.022 (0.027)	−0.009 (0.022)	0.013 (0.036)
<i>Early-life experience: # of mo. with disaster in the first 1000 days</i>			
	−0.065*** (0.024)	−0.008 (0.022)	−0.047 (0.033)
Female	−0.417*** (0.061)	−0.419*** (0.061)	−0.418*** (0.061)
Mother is alive	0.321** (0.160)	0.324** (0.160)	0.323** (0.160)
Father is alive	0.226** (0.105)	0.225** (0.105)	0.226** (0.105)
Mother is alive × living in same HH	0.057 (0.080)	0.056 (0.080)	0.056 (0.080)
Father is alive × living in same HH	−0.217*** (0.061)	−0.216*** (0.061)	−0.216*** (0.061)
Mother ever educated	1.337*** (0.082)	1.343*** (0.082)	1.341*** (0.082)
Mother ever educated × has secondary	1.000*** (0.067)	0.997*** (0.067)	0.998*** (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 $t \times$ 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) Flood	(2) Severe disaster	(3) Severe flood
# of mo. with disaster in mid-child life			
× Age 7–9	0.016 (0.050)	−0.006 (0.039)	0.069 (0.061)
× Age 10–12	−0.034 (0.042)	−0.019 (0.026)	0.021 (0.051)
× Age 13–14	−0.030 (0.036)	−0.026 (0.026)	0.023 (0.047)
# of mo. with disaster in the first 1000 days			
× Age 7–9	−0.087 (0.053)	−0.031 (0.029)	−0.052 (0.059)
× Age 10–12	−0.001 (0.027)	0.016 (0.024)	−0.002 (0.041)
× Age 13–14	−0.023 (0.031)	−0.028 (0.030)	−0.040 (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 $t \times$ 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 (0.030)	−0.013 (0.024)	0.022 (0.038)
× Female	−0.027 (0.028)	−0.002 (0.022)	0.003 (0.036)
# of mo. with disaster in the first 1000 days			
× Male	−0.069*** (0.026)	−0.017 (0.024)	−0.064* (0.035)
× Female	−0.061** (0.026)	0.003 (0.022)	−0.030 (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 $t \times$ 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.

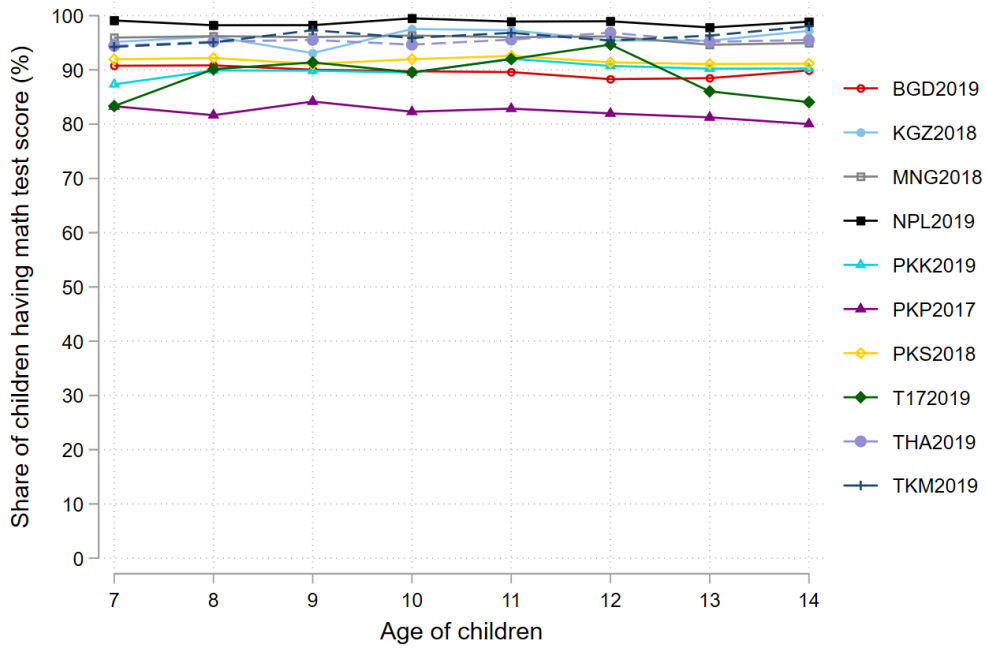
Table C.16: Disaster and math test score, heterogeneous effects across gender and age groups using other disaster intensity types

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

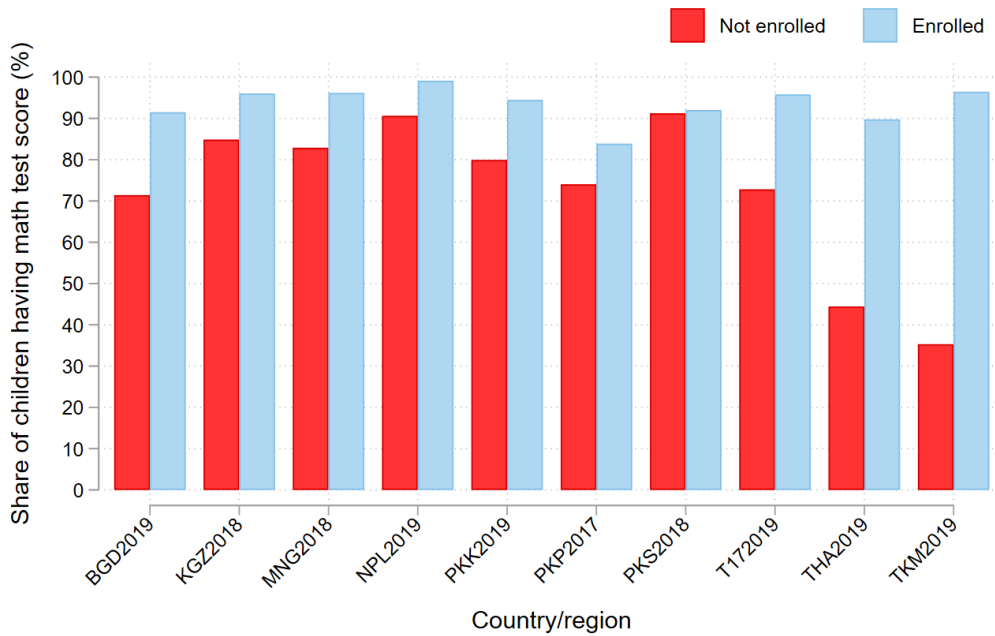
Note: For the disaster intensity type, we consider type A as any type of disaster, B as only flood, C as severe disasters which is defined as causing more than 50 people dead or injured or 5,000 people affected. Type D combines B and C considering only severe flood. In the main results, we use type A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



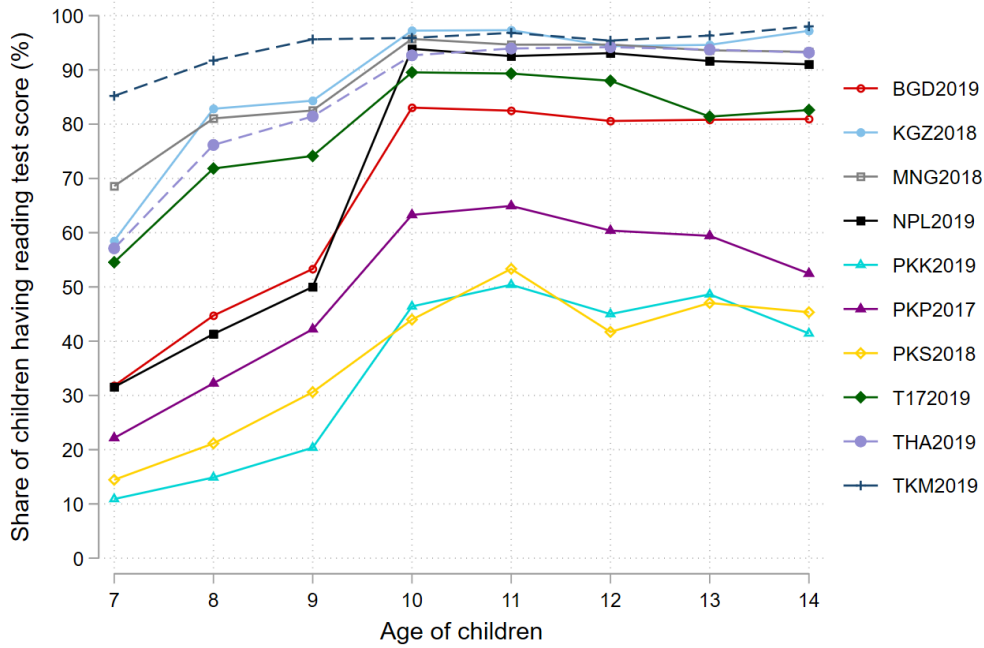
(b) Math Test Sample Size by Enrollment Status in Current Year Across Countries



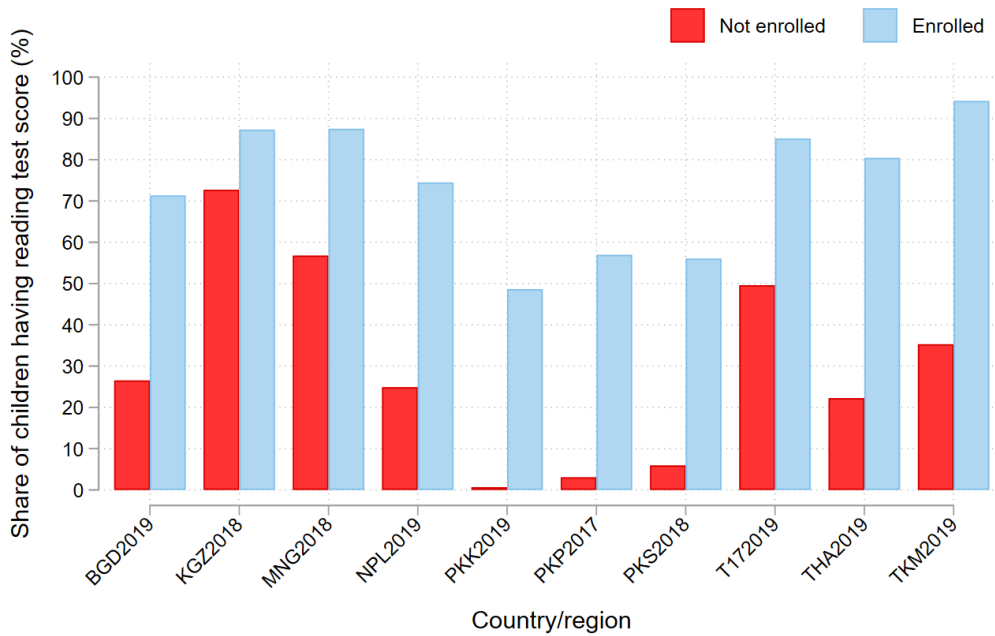
Note: Fractions show share of sample by age and country reporting math test score, consistent share across ages, some variation across countries. We notice whether the child has Math test Score is related to if she is enrolled in school in the current period. We find much larger share with math test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

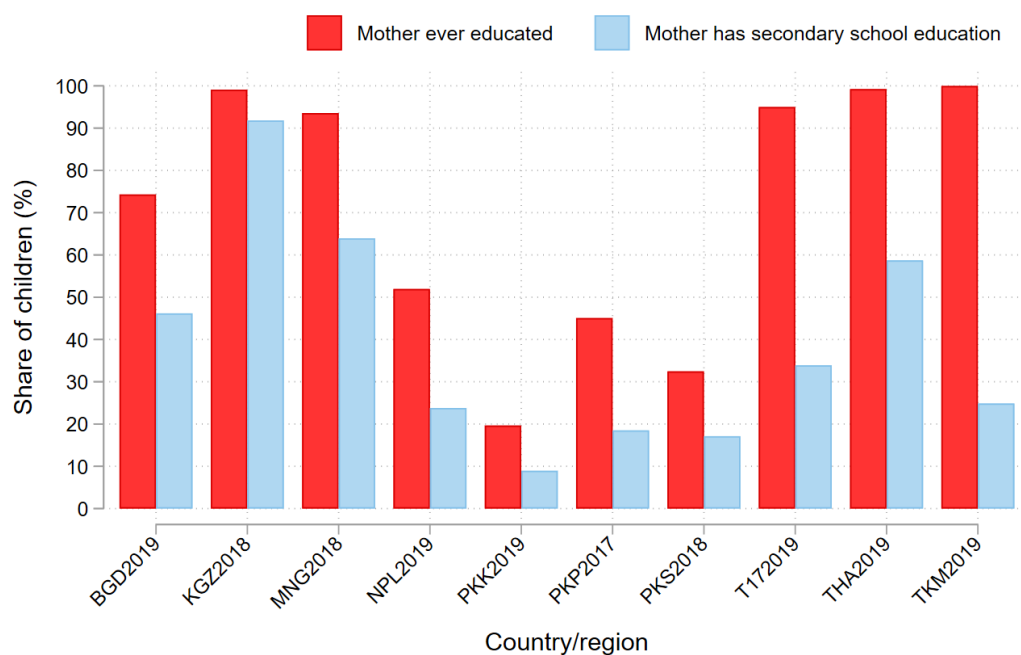


(b) Reading Test Sample Size by Enrollment Status Across Countries



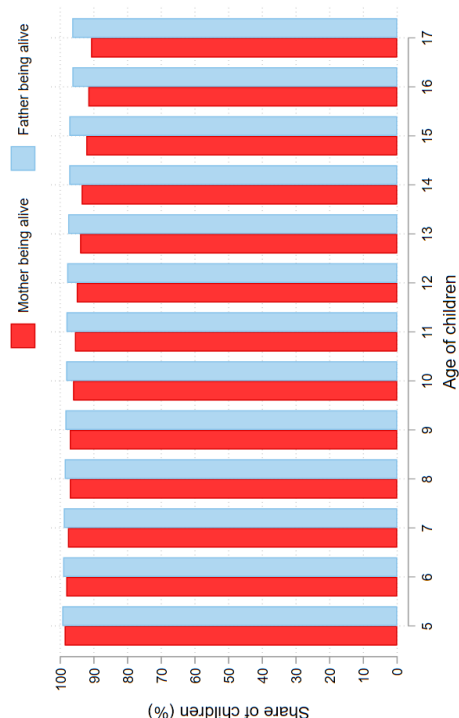
Note: Fractions show share of sample by age and country reporting reading test score, consistent share across ages, some variation across countries. We notice whether the child has reading test Score is related to if she is enrolled in school in the current period. We find much larger share with reading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

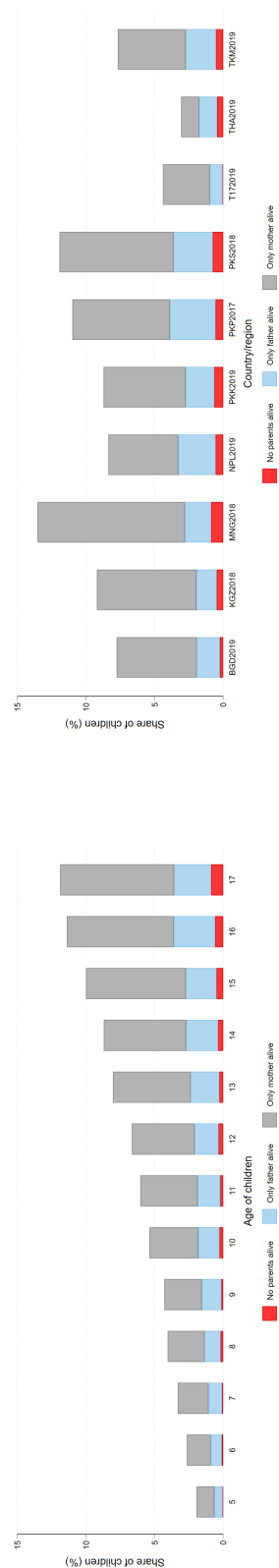


Note: This table show (1) share of children whose mother has had any kind of education (2) share of children whose mother has secondary school education by countries. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** 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, **TKM**).

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



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

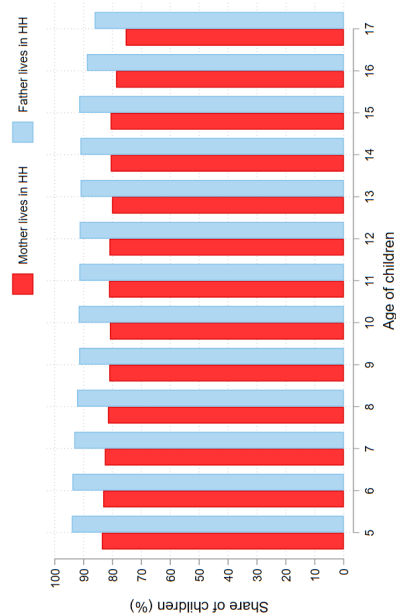


(c) Share of Children (Age ≥ 12) with Both or One Parent Alive by Countries

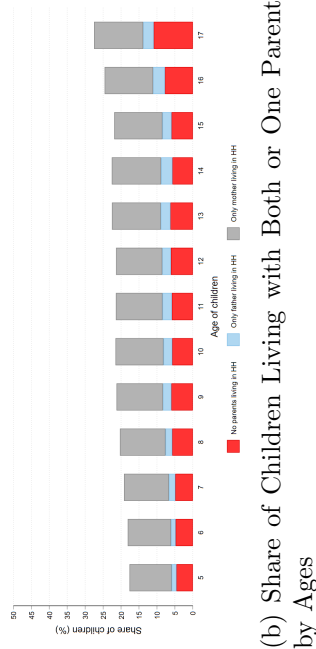
(b) Share of Children with Both or One Parent Alive by Ages

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

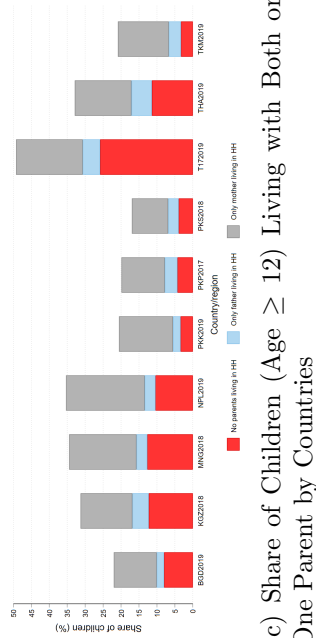
Figure C.5: Share of Children Living with Parents



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



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

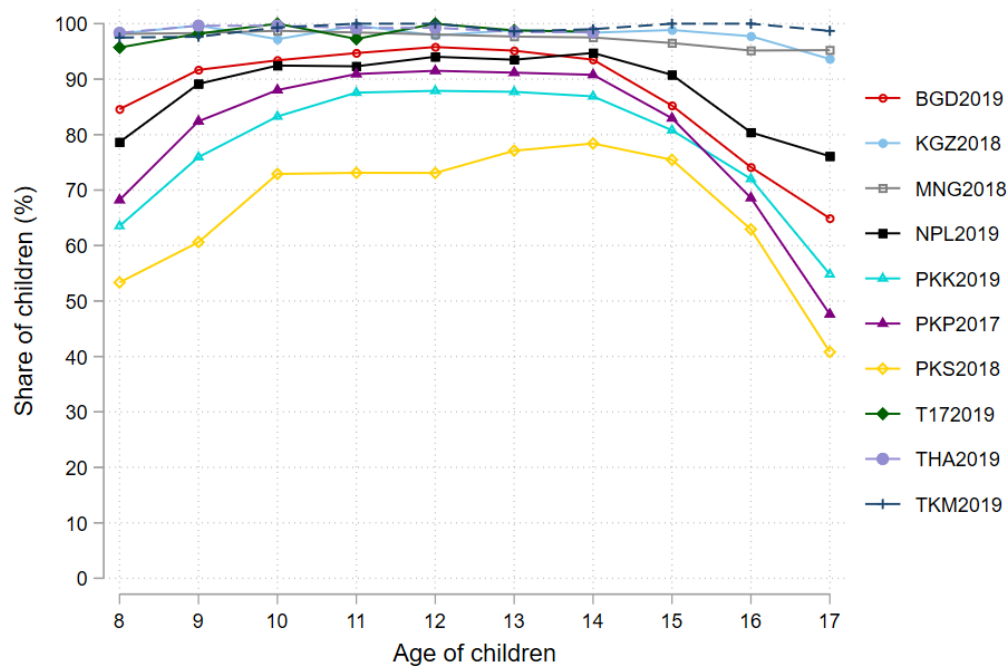


(c) Share of Children (Age ≥ 12) Living with Both or One Parent by Countries

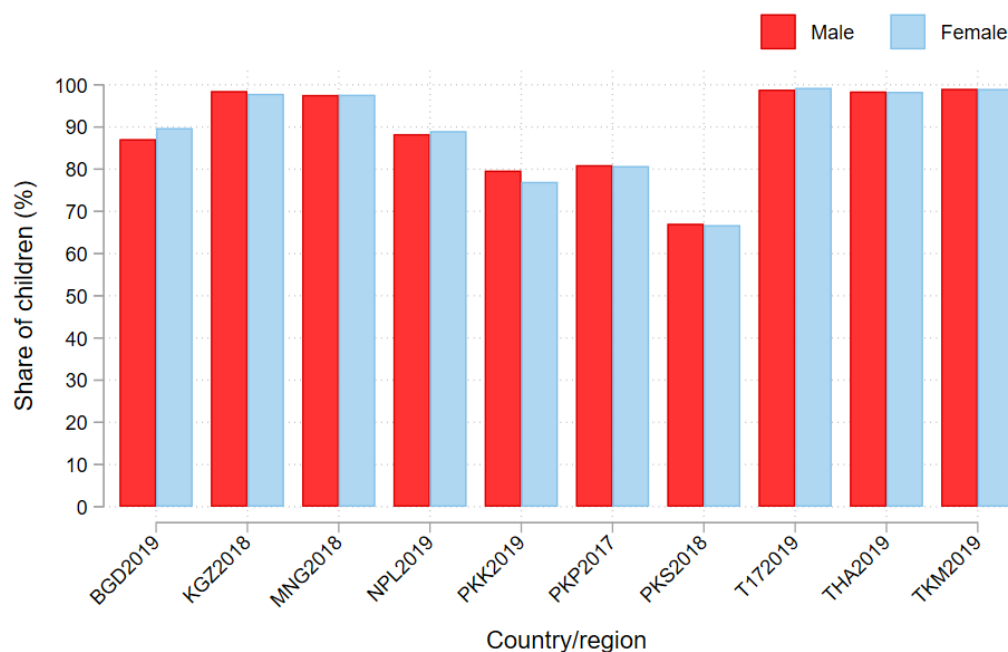
Note: Panel (a) shows the share of children living with either mother or father by ages. Panel (b) and (c) show the share of children living with both parents or one of them by ages. The four categories include living with both parents (not included in the bar), with just mother, with just father, not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

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

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



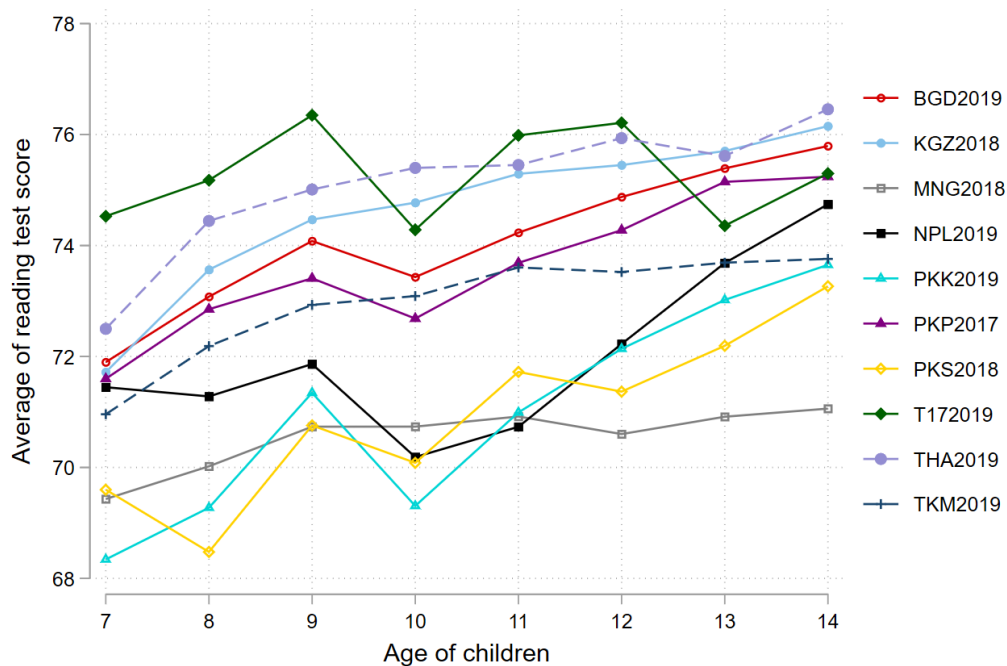
(b) Progression Rate in Last Year by Gender and Countries (\geq age 8)



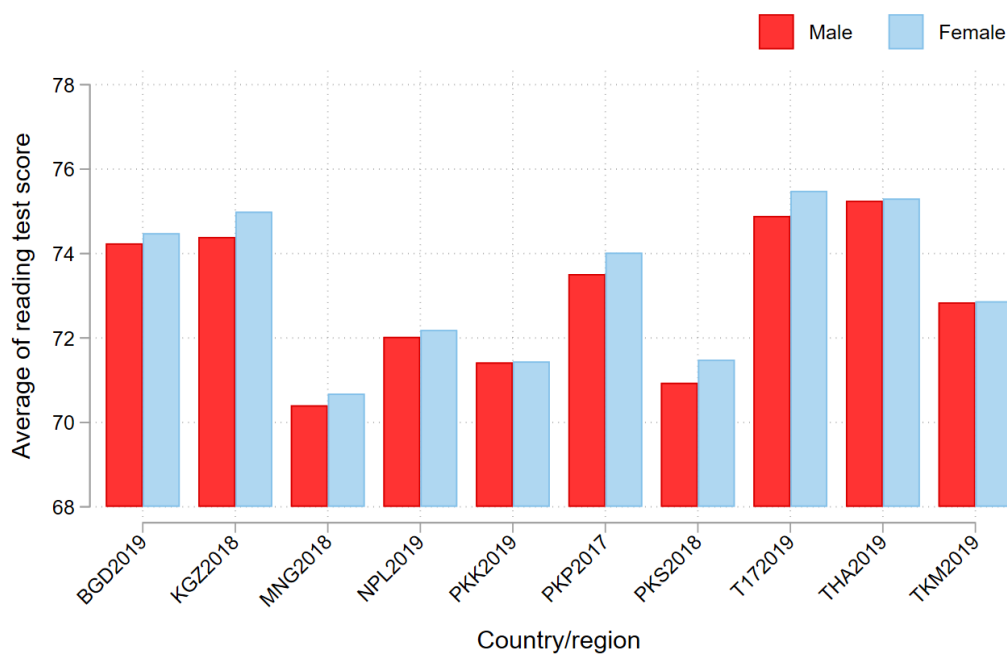
Note: The table shows progression rates. Progression is equal to 1 if a child attends a grade and successfully completes the grade, leading to an increase in grades completion by 1 years. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber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

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, **TKM**).