Are Disasters Disastrous for Learning? Evidence from Seven Asian Countries

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

December 23, 2023

Please click here for latest version.

Abstract

The Asia-Pacific region is the most disaster-prone world region. Educational impacts of natural hazards could be greater for children if their families have fewer resources with which to cope with disasters or if the institutions to which they have access are less resilient. Focusing on children ages 5 to 17 in seven countries in Asia, we link survey data on children (Multiple Indicator Cluster Surveys, MICS 6, using household-specific survey dates and smallest available geo-identifiers) to time- and geo-coded disaster variables (EM-DAT). We create time-varying intensity variations in disaster exposure for each child's life cycle, with a focus on the disaster experience in early life (first 1000 days of life), recent years prior survey month, and mid-child life (the time span in between). We estimate the heterogeneous impacts of natural disasters on school enrollment and cognitive achievements for children along age, gender, and SES gradients. Especially, we examine the importance of children's ages when exposed to natural-disaster shocks for the sizes of the impacts in seven Asian countries. We find a significant negative effect of early life disaster exposure on enrollment and math skills, especially for boys, but weaker or no corresponding effects for recent disaster exposure. There is a weak but increasingly negative relationship between recent disaster exposure and enrollment as children age. There is a more persistent negative relationship between early disaster experience and enrollment through the school-going ages. School enrolment of children in both genders having experienced in early life any type of natural disasters is found to be affected negatively. Although the impact on school enrolment figures is greater for boys than girls, the cognitive performance of girls are harder hit than the boys in older cohort (age 13-14). Age pattern of enrollment and learning effects of disaster exposure differ across national settings.

Keywords: Education, health, natural disasters, learning outcomes

JEL: I24, I25, I28

*Yujie Zhang: Department of Economics, University of Houston, Houston, Texas, USA (yzhang187@uh.edu); Jere R. Behrman: Departments of Economics and Sociology and Population Studies Center, University of Pennsylvania, Philadelphia, Pennsylvania, USA (email: jbehrman@sas.upenn.edu); Minhaj Mahmud: Economic Research and Development Impact Department, Asian Development Bank, Mandaluyong City, Philippines (mmahmud@adb.org); Emily Hannum: Department of Sociology and Population Studies Center, University of Pennsylvania, 3718 Locust Walk, Philadelphia, Pennsylvania, USA (hannumem@sas.upenn.edu); Fan Wang: Department of Economics, University of Houston, Houston, Texas, USA (fwang26@uh.edu); We gratefully acknowledge support to develop this project via a Quartet Pilot Research award funded by the Population Studies Center at the University of Pennsylvania and support from NSF PIRE Grant 2230615: Climate risk, pollution, and childhood inequalities in low- and middle-income countries.

1 Introduction

Between 1970 and 2019, the UN 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 floods, drought, and extreme weather events (Ipcc 2022). Climate change-induced disasters pose a particularly serious threat in the Asia-Pacific region, which is the world's most disaster-prone region (United Nations Economic and Social Commission for Asia and the Pacific (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 (United Nations 2021).[1] A recent report indicates that in 2022, over 140 disasters struck the Asia-Pacific region, leading to over 7,500 deaths, affecting over 64 million people, and causing economic damage estimated at US$ 57 billion (United Nations Economic and Social Commission for Asia and the Pacific (UN-ESCAP) 2023).

Children are potentially 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). Climate change tends to interact with "non-climatic stressors and entrenched structural inequalities to shape vulnerability" (Olsson et al. 2014). Climate and environmental shocks can create vicious cycles of social change by worsening existing poverty and exacerbating various kinds of inequalities (Olsson et al. 2014). Negative effects are correlated with social disadvantages (Fuller 2014; Cutter, Boruff, and Shirley 2003; Zahran et al. 2008). Children from socially, economically, or politically disadvantaged regions could be more vulnerable to ill effects when exposed to natural disasters because families in such regions have fewer resources with which to cope with disasters, or because the institutions to which children or families have access are less resilient.

Most existing studies of natural disasters' effects on children have focused on tracing out the impacts of a specific large-scale disaster (Cho and Kim 2023; Tian, Gong, and Zhai 2022; Ciraudo 2020; De Vreyer, Guilbert, and Mesple-Somps 2015; Gibbs et al. 2019). In this paper, we provide one of the first cross-nation and cross-disaster analysis of effects of disruptive natural disasters on human capital accumulation, taking into consideration each child's individual-specific history of disaster exposures. Specifically, we link together survey data on children ages 5 to 17 from seven developing economies in Asia from the Multiple Indicator Cluster Surveys (UNICEF 2010) together with time- and geo-coded disaster variables from the EM-DAT disaster dataset (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 temperature. Exploiting variations in MICS survey locations, variations in location-specific survey timing, as well as variations in child age composition among children surveyed in each location and each month, we develop a novel

1. 45 per cent of these disasters were associated with floods and 36 per cent with storms (United Nations 2021).

dataset that provides time-, age- and location-specific disaster exposure histories for children. Leveraging our unique dataset, we provide the first estimates of the effects disasters on human capital accumulation that distinguishes between the separate effects of current and earlier in life disaster shocks.

Impacts of climate disasters on children's lives are multifaceted. Natural disaster shocks may impact children's learning process through educational disruption. For example, in 2010 Pakistan, 11,906 schools with more than one million children were affected by natural disaster 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 its effects on school operations, disasters can also lead to negative income and health shocks. These shocks could reduce household resource availability for schooling, children's physical capacity to attend school, and increase the opportunity costs of schooling as children compensate for lost parental income by taking up greater household and wage work responsibilities (Alam 2015; Bandara, Dehejia, and Lavie-Rouse 2015; Guarcello, Mealli, and Rosati 2010). 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 as much care for children at home after disasters strike.

Short term impacts on enrollment could lead to long term effects of disasters on human capital development and accumulation for children. Hence, we consider not only the impacts of disaster shocks but also that of shocks occurred in early life on human capital accumulation. Due to negative health and economic impacts, changes in prenatal stress caused by natural disasters have negative effects on educational or economic performance later in life (Andrabi, Daniels, and Das 2021; Charil et al. 2010; Fuller 2014). Combining this with the fact that central nervous system and brain undergo rapid growth between 8 and 25 weeks post-conception which is essential for cognitive development and performance (Almond, Edlund, and Palme 2009), we focus on the period from the moment they are conceived until they reach age two (first 1000 days of life) to construct early life shocks. This is an indirect dimension through which natural disaster shocks in early life affects educational outcomes. Abnormal health status in early life could in long run exert negative effect on subsequent IQ, lower the cognitive development as well as increase the cost of children attending schools compared to their peers as they may need to visit hospital and miss classes more.

We link survey data on children from Multiple Indicator Cluster Surveys and disaster data from EM-DAT to study the the effects of disasters on enrollment and test scores for children ages 5 to 17 in seven developing economies in Asia. 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 when the age at which children were exposed as well as their current age at the time of enrollment or test score measurement. Given correlation in disaster exposure across time and within location, the joint

2. The impact of disruptions to traditional 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.

consideration of disasters exposed by a child over her lifetime 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 a child'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 model educational achievement—MICS-administered numeracy 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, first 1000 days of life, time between the first 1000 days and the most recent 2 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.

Results 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 exposure. Heterogeneity analysis shows that there is a weak but increasingly negative relationship between recent disaster exposure and enrollment as children age, while a more persistent negative relationship between early disaster experience and enrollment is found through the school-going ages. School enrolment of children in both genders having experienced in early life any type of natural disasters is found to be affected negatively. For the relation between exposure to natural disasters and math test scores, it is also weak for recent shocks yet strong for exposure in early life. Age pattern of learning effects of disaster exposure differs across national settings. Although the impact on school enrolment figures is greater for boys than girls, the cognitive performance measured by MICS-administered numeracy test of girls are harder hit than the boys in older cohort (age 13-14).

Related Literature This paper contributes to the existing literature in several ways. First, as we not only study the short time disaster shock but also the early life shock, we contribute to the large group of literature on addressing the immediate and lasting effects of disaster shocks in early life. There are negative health and economic impacts of changes in the early-life environment (Andrabi, Daniels, and Das 2021) and prenatal stress caused by natural disasters has been related to abnormal cognitive outcomes (Charil et al. 2010). For instance, children exposed to hurricanes *in utero* are found to have lower scores in third grade (Fuller 2014).

A larger group of study focuses on the effect of natural disasters on child development through the dimension of health status instead of educational outcomes such as the study on fetal-origins hypothesis in short-run and long-run using 1918 Influenza Pandemic (Almond and

Mazumder 2005; Lin and Liu 2014). Infants' anthropometric outcomes such as fetal loss and birth weight is found to be negatively effected by the *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, this early life shock has negative impact on 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 weight and lower gestational age at delivery (Rondó et al. 2003; Sable and Wilkinson 2000; Torche 2011). Our paper by directly using school enrollment and test score data for children is one of the few studies establishing the lasting effect of having experienced disaster in the first 1000 days on schooling attendance and learning outcomes. This highlights the need to more specifically support to children affected by disasters in their early years on both health care and educational resource.

Second, we explore heterogeneity globally and locally with large sample and consider multiple disasters. Some early papers linking the parental stress which can be yielded from exposure to natural disasters use very small samples (Charil et al. 2010; King and Laplante 2005; Weinstock 2005). Meanwhile, most of the literature studying environmental effect on educational outcomes of children focuses on either temperature or rainfall, but not much estimates the effect of general kinds of natural disasters.

Studies on impacts of disasters on educational outcomes usually use one disaster in one country rather than multiple types of disasters. These include the study showing the negative impact of 2017 Pohang earthquake in South Korea on college entrance exam scores (Cho and Kim 2023) and the one showing that lower educational attainment in adulthood is associated with high-intensity exposure to 1976 Tangshan earthquake (Tian, Gong, and Zhai 2022). Ciraudo (2020) tracks the academic performance of a cohort in Chile affected in early life by the 1985 earthquake and De Vreyer, Guilbert, and Mesple-Somps (2015) show negative educational outcomes after large income shock after 1987-89 locust plague in Mali using census data. Variation in exposure to a major bushfire in Australia is exploited by Gibbs et al. (2019) and they find that academic performance was reduced in schools with higher exposure.

There are limited papers on broad groups of disasters. However, those using multiple types or groups of disasters do not focus on educational outcomes in developing countries. Opper, Park, and Husted (2023) use data from the United States and find that natural disasters impact a region's human capital both via reductions in learning for students who stay in stay school and in the years of schooling completed. Simeonova (2011) also uses US data and Currie and Rossin-Slater (2013) studies groups of hurricanes in Texas yet both focus on pregnancy and birth outcomes. By using a large sample covering more than 140 thousands of children in seven Asian countries and a global record of natural disasters, we are able to estimate the multiple disaster shocks effects and our results should be easier to be generalized.

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 numeracy test scores. In Section 5 we present and interpret the main results. Section 6 concludes. Tables and figures referenced with a prefix being 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 educational outcomes effect of natural disasters. MICS is a global multi-purpose survey program conducted by the United Nations Children's Fund (UNICEF), and it provides statistically sound and internationally comparable data on the situation of children and women. From mid-1990s until now, 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. 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 unit of analysis is household and individual. 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 the household.

There is growing literature using MICS. It is a good resource for country- or sub-national level analysis. The recent rounds are used to study the effect of COVID-19 school closures effect on cognitive skills and responses of low- and lower-middle-income countries (Alban Conto et al. 2021). DHS and MICS data are used together to compare multiple estimates of under-5 mortality in sub-Saharan Africa (Eilerts et al. 2021). The fruitful water-quality module is used to quantify the availability and microbiological quality of drinking water across 20 countries (Bain et al. 2020). Relationship between higher probability to be positive in disability screening and poorer nutrition and fewer early learning of children aged 2-9 years is found in 18 countries (Gottlieb et al. 2009).

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. The data was downloaded from the website 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 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))[3].

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

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

particularly high even they are hit by disasters at same severity level. For example, Bangladesh 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 (Siddiqui 2015). Table 1 provides country-specific data collection window, sample size, and summary statistics for some key variables.

2.2 Data on Disasters

Our natural-disaster variables are mainly constructed from EM-DAT (1900-2023). The date of interview is 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 and create the time-varying intensity variations in disaster exposures for each location as well as individuals.

EM-DAT is an international database compiled by the Centre for Research on the Epidemiology of Disaster (CRED) with comprehensive information on natural disasters which led to the 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. Entries in this data are based on any of the following: (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 researchers to link them with other databases such as Dartmouth Flood Observatory, Global Volcanism Program, and USGS.

EM-DAT is a rich and the most widely employed resource for study impact 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 presents that more than 60% of 64 primary studies published in 2000–2013 have used EM-DAT (Lazzaroni and Bergeijk 2014). For example, it has been used to estimate the average outcomes in 73 nations (Kahn 2005), 89 countries (Skidmore and Toya 2002), 108 countries (Felbermayr and Gröschl 2014), and for 109 countries (Noy 2009) over several decades. The effect 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 on various types of disasters in EM-DAT, researchers are able to generally aggregate different disasters occurring in certain location and time span 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 raw data spreadsheet file, each row is one disaster and columns are information associated with this one single 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.

We obtain geographical and temporal information of each disaster from context variables. For geographical information, country name, ISO Code, region, continent, and river basin are considered. Location of epicenter of earthquake is provided for earthquake. Admin level code and location names of all locations affected by this 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.

2.3 Measures

2.3.1 Parental and Household Characteristics

For socioeconomic status (SES), we consider the following measures. First, we observe the age and education level of parents. Then, having parents alive or not can be fundamental for if the child has any support from parents. Furthermore, the cohabitation status is constructed based on if the child is living with mother or father or both. MICS6 also provides relative household wealth instead of direct information on financial background on household level. There is a combined wealth index for each household which is within-country relative, constructed from a principal components analysis based on the ownership of consumer goods, facilities, and dwelling characteristics (Emerson and Llewellyn 2022). It is a weighted score designed to capture the underlying long-term wealth and households are also divided into five wealth quintiles, with the highest quintile representing the wealthiest 20% of households, and the lowest quintile representing the poorest 20% of households. These variable are often used as socioeconomic status (SES) allowing us to investigate the family background, living environment, and financial insecurity of children. Other demographics such as parents' age at children's birth, children's age, gender, and birth number are also potential modifier behind the heterogeneous impacts of natural disaster on children education outcomes.

2.3.2 Educational Outcomes

Enrollment and Attainment The educational outcomes will be the school enrollment, attainment, grade progression, retention, and the foundational learning skills for children age 7 to 14[4]. 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 and last school year. Hence, we are able to construct the indicators for ever enrolled, enrolled this year, and enrolled last year, respectively, as well as the highest attainment by the

4. We provide more details on measures construction in Online Appendix section.

survey date, attainment at start of last school year, and attainment at start of this school year. The grade progression is indicator being one if one child makes progression in last school year conditional on being enrolled in last year. The retention indicator shows that if the child is repeating the grade in this school year conditional on being enrolled in both last school year and this school year. We show the average enrollment rate at region level[5] for each countries in Table 1.

Test Scores 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. There are several components in reading test including recognizing words and story comprehension. For math test, scores on recognizing symbols, comparing numbers, numbers adding up, and next number identifying. We first check the availability of test score for each child as there is a chance that the fact of child being able to take and complete the test itself shows the cognitive skills development. Then we construct the total test score for reading and math separately as measure of cognitive skills.

2.3.3 Disaster Shock

Binary and Continuous Measures of Disaster Intensity in Particular Time Spans Using location names affected by each disaster recorded in EM-DAT data, we are able to link disasters with each location in MICS data. 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, $DI^p_{il,mo}$. 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 lives in that location l, we assign this disaster shock intensity to her. Then, by calculating $DM^p_{il,j}$, the number of months experiencing disaster for child i in location l during span of time j, we are able to obtain the binary indicator for existence in time span j of type p disaster intensity, which is denoted by $DB^p_{il,j}$.

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

Critical Period in Life-Cycle We focus on critical period in life-cycle to construct the individual-specific particular time spans. These include the most recent year prior survey month (including survey month), the year before the most recent year, the first 1000 days of life (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. In fact, interview date is observed for all children as well, but

5. 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.

we choose to construct the disaster shocks at month level because birth date is not observed for all and more importantly, starting and ending date of disasters are not largely recorded making it difficult to match disasters with individuals' life cycles at date level. The earliest year the child was born in is 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 have information on start year and start month of only three disasters is missing, yet 86 disasters are not recorded with start day. The end year of all disasters are observed with end month of only ten disasters missing, yet end day of 87 disasters are missing.

Types of Disaster Intensity For the disaster intensity type denoted by p, 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 possibility for robustness check on disaster experience construction.

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 sixth round of the MICS survey. Some important points are noteworthy from MICS data for each country. The data provides information on enrollment, progression, retention, and foundational learning assessment test scores on numeracy and reading skills for these kids. However, the sample size differs for the progression, retention and test scores variables since all children are not simultaneously observed as enrolled in the successive years (survey year and the preceding year) and that only children aged 7 to 14 years participate in the foundational leaning assessment module of the survey subject to their availability at home as well as parental consents. Again, score for reading is observed for a lower percentage of the children in these age groups.

In Table 2, we show summary statistics for all children of all variables in three panels. The total sample includes 144,471 children, with 46% being female. We present the distribution of the sample by country and ages in Figure 1. The average enrollment rate in the school year when children are surveyed is 90%, as the enrollment rate in the past year is lower. We notice that less than half of children do not have valid reading test score, but math test score are available for more children. In Appendix Figures C.1 and C.2, we provide details by age, country, and enrollment status of the share of sample between age 7 and 14 with recorded scores for the numeracy and reading test scores, respectively. We find higher availability of numeracy scores among students currently enrolled.

3.1.2 Parental and Household Characteristics

Table 2 shows that father age is on average 6 years larger than mother age, and the rate of father ever educated is slightly higher than the rate of mother. But it is also noticeable that father information is collected less than that of mother.

We find larger share of children with mother living in the same household than fathers, and more children with mothers who are alive. In Figure 2, we present these statistics by child ages. We find that by age 17, about 9 percent of the children in the sample no longer have a father who is alive and 25 percent of the sample are no longer living with fathers. In contrast, the share of children with mothers who are alive is above 96 percent across all ages, and share of children living with mothers is larger than 85 percent across all ages.

In Appendix Table C.2 and Figure C.3, we break the sample by countries and show information on mother's education level and whether children live with parents across countries. In Turkmenistan, Kyrgyzstan, Thailand, and Mongolia, the share of mother who have been ever educated (ever-enrolled) is larger than 95 percent; In contrast, in Bangladesh and Pakistan, the shares are 74 and 36 percent, respectively. 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 share of mothers with higher than middle school education is equal to half of the share of mothers who have ever been enrolled in school.

3.1.3 Educational Outcomes

In Panel 1 of Table 2, we show overall summary statistics for educational outcomes, including variables on enrollment this year, last year, attainment (grades completed) at the start of of the school year, school progression (conditional on enrollment whether a child successfully completes the grade), and reading and math test scores. 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 age 14 are surveyed; in other countries, averages are based on all children between age 5 to 17.

Educational Attainment Educational attainment is defined as the highest completed grade (maximum number of years of schooling) by a child at the current age. Results on attainment by age and country are shown in Figure 4. Average maximum attainment (AA) for children (4-17 years old) varies by countries, with Mongolian children having the highest and children from Pakistan having the lowest average attainment in years of schooling. We note the averge 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, the average attainment, girls out perform boys in Bangladesh, Kyrgyzstan, Mongolia.

Related to the highest grades completed variable, we also present in Figure 3 the share 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 by age 17 in Sindh Province.

Enrollment In Figure 5, we present enrollment status in the survey year. In Figure 6, we use the enrollment status in this year and last year jointly to consider the heterogeneous transition probabilities from across enrollment status over one year.

Girls' current enrollment compared to boys is higher in case of 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 all countries. Additionally, the share of children who comes back to enrollment after not enrolled in the last year decreases with age and falls below 10 percent after age 11. The share of children who are enrolled in the last year and continue to enroll in this year is greater than 95 percent up to age 14, and falls to 88 percent by age 17.

Retention and Progression We denote child retention by an indicator (=1) if a child currently enrolls a grade identical to one from last year. Results on retention by age and country are shown in Figure 7. We find that generally older children are more likely to be retained, with the highest retention rates reported in Bangladesh and Pakistan. Also, this is higher for boys, on average, from Bangladesh and Nepal and for girls from Pakistan compared to other countries.

Additionally, We define child progression by the indicator (=1), if a child successfully progress comparing to the last year and start of the the current survey year. Results on progression by age and country are shown in Appendix Figure C.6. Interestingly, average progression declines as children age and that only three countries record 100 progression for children above 8 years. Children from Pakistan only have 70 to 80 percent progression rate and girls slightly outperform boys in Bangladesh and Nepal.

Test Scores Children's educational outcome are measured as foundational numeracy and reading skills. Average numeracy and reading skill test results by age and country are shown in Table 3 and Figures 8 and C.7. Aggregate math scores denoting numeracy 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 nature of the test administered to children of all ages, not surprisingly, older children perform relatively better than younger children. As shown in Figure 8, for the numeracy 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 numeracy test scores as children age. Children from Pakistan have the lowest numeracy test scores, and average scores have slow growth as age increases. In particular, average numeracy 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 past 12 months before interview month, in total, 70% of children in all the seven countries experienced at least one disaster, and on average, there was natural disaster in about 1.08 months within that 12 months. The share of children experiencing any disaster in 10 years prior to most recent year is almost 1, meaning that almost every location in our sample in those location-specific 10 years have been hit by at least one disaster regardless of type of disaster.

In Table 4, furthermore, we show variations in disaster exposure across countries. For example, there are no disaster recorded for Turkmenistan during the spans of time we are considering, while for Bangladesh, 88% of children experienced disaster in past 12 months.

Additionally, we show in Figure 9 the share of location/months experiencing disasters of different types by calendar month and location. 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 outcomes outlined earlier based on jointly exploiting temporal variations in disaster exposures within the same location as well as intensity variations in disaster exposures across similar locations at the same time.

Our analysis for the impacts of disaster shocks on educational outcomes focuses on two groups of outcomes: educational outcomes for children and organizational factors. For educational outcomes, we study the heterogeneous impacts of natural disasters on grade progression, school enrollment, education attainment and cognitive achievements 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 educational outcome including enrollment and test scores (each is denoted by E and S, respectively, in following sections). We use separate letters to denote 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 month and child ages within sub-national locations. Specifically, we have t to denote the school year one child is in when taking 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 one child in the interview month. For example, if one child is born in 2000 Jan, and got interviewed in 2017 Jan, then she is $g = 17 * 12$ months old in the interview month. Then $g - 12$ denotes the age in months in the most recent year before interview month.

Enrollment and Recent Disasters In models of educational enrollment for children in the context of low- and middle-income countries, households make binary school enrollment decisions given trade-offs between going to school and alternatives of child staying at home or working (Attanasio, Meghir, and Santiago 2012; Todd and Wolpin 2006; Casco 2022). Without enrollment, the child can not make additional grades completion progress; with enrollment, the child faces some probability of passing the attending grade and increasing her educational attainment (Attanasio, Meghir, and Santiago 2012). The gains from enrollment comes from the expected value of increases in educational attainment and achievement by the start of the next period; on the other hand, 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 considers 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 of 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 are able to 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 shock 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 disaster) of enrollment. These recent disaster shocks might also reduce the gains from enrollment by decreasing 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, other disaster shocks that arrived later might not impact enrollment but mainly impact progression.

Second, we also consider early childhood disaster shocks, which might have had formative impacts on the cognitive and noncognitive 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 observable to 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 relation between enrollment and disaster experiences, we estimate an enrollment equation:

$$\begin{aligned} E_{ilt} = &\alpha_0 + \psi_0 \cdot E_{il,t-1} + \psi_1 \cdot A_{ilt} \\ &+ \sum_{j \in \text{TimeSpan}} \alpha^p \cdot D^p_{iltj} \\ &+ \theta X_i' + \mu_l + \mu_{g_i(t)} + \mu_t + \epsilon_{ilt}, \end{aligned} \tag{2}$$

where TimeSpan $= \{m12to1, first1000days\}$ with $m12t1$ representing the most recent year up to the survey month and $first1000days$ capturing the first 1000 days of life. $E_{il,t-1}$ 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^p_{iltj} denotes the natural disaster shock of type p[6] received by child i in location l at time t, looking back at prior time span j.

We control for a vector X of individual and parental observables including parental age, 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 is at the same level (or lower) of geographical aggregation as the disaster variable, child age fixed effects $\mu_{g_i(t)}$, and also survey time fixed effects, μ_t.[7]

Controlling for these fixed effects and observables are critical to 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 locations 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 over time shifts in secular trends.

Achievement and Life-cycle Disaster History We model educational achievement—MICS-administered numeracy and reading test scores—as the output of human capital production 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 and at different stages of a child's life-cycle.

In contrast to child, family, school, and neighborhood inputs, disasters are not endogenous choices made by agents. 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. In our setting here, we only consider the history of disasters and not other inputs. This means that our estimates for disasters will include the direct effects

6. As described in data section, there are two measure for disaster intensity, as well as four shock intensity type p. For certain disaster intensity type, the disaster shock can be either binary indicator or continuous measure, capturing the the number of months exposed to disaster.

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

of disasters as well as indirect effects due to endogenous changes driven by disaster 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:

$$S_{ilm} = \alpha_0 + \sum_{j \in TimeSpan} \alpha^p \cdot D^p_{ilj} + \theta X'_i + \mu_{c,A_i(m)} + \mu_l + \mu_{g_i(m)} + \mu_m + \epsilon_{ilm} \ , \tag{3}$$

where S_{ilm} is the score on the MICS-administered test achieved by child i in location l at survey month m. We succinctly consider the child's life-cycle of disaster exposures in three parts, TimeSpan $= \{m12to1, age25mtolastyear, first1000days\}$, which contains disaster exposure in the most recent year, the years between the most recent year and the first 1000 days of life, and in the first 1000 days of life. 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 $\alpha^j_{g_i(m)}$:

$$S_{ilm} = \alpha_0 + \sum_{j \in TimeSpan} \alpha^j_{g_i(m)} \cdot D^j_{ilp} + \theta X'_i + \mu_{c,A_i(m)} + \mu_l + \mu_{g_i(m)} + \mu_m + \epsilon_{ilm} \ , \tag{4}$$

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

Our estimation strategy exploits heterogeneities in disaster 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 $\alpha^j_{g(i,m)}$ for each age. We implement Eq. (4) by allowing for heterogeneous disaster effects for children across different age groups (7 to 9, 10 to 12, and 13 to 14), with the assumption that the effects of disaster histories are homogeneous within each age group 3.

5 Results

5.1 Enrollment and recent and early disaster experiences

We estimate Eq. (2) using 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 disaster in the first 1000 days of life 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 of life exposed to EM-DAT disaster reduced enrollment by 0.1 percentage points. There is significant heterogeneity in the number of months exposed to early life disasters across and within country, 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 disaster 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 (years of education) completed at the start of the current school year (at the start of t). We find strong positive association 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 3, aggregating across countries and ages, we find girls have 0.6% lower enrollment than boys. We also find the 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 1.4%, and having a mother who is alive but not living in the same household decreases enrollment by only 1.5%. In contrast, having a father living in the same household is associated with a 0.8% increase in enrollment, but having a father alive but not living with the household is associated with a larger increase in enrollment by 1.3%.

5.2 Heterogeneous disaster effects on enrollment 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 5 differ substantially across ages, gender and countries. In this section, we continue to estimate Eq. (2) using linear probability model by regressing enrollment this year and disaster experiences, but explore heterogeneity by child age groups in Table 6 and heterogeneity by joint child age and gender in Table 7. We further present heterogeneity by joint child age and country groups in Table C.4.

In both Table 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 admin 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 size in each.[8] Within each cluster, there are variations in child ages and some limited variations in survey month. 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 month within cluster to identify the effects of recent shocks.

Overall, we find a weak and increasing negative relationship between recent disaster and enrollment as children age and we find a more persistent negative relationship between early disaster experience and enrollment throughout school-going ages. We also find that the effects of recent and first 1000 days disaster shocks have different profiles of life-cycle impacts across gender. Across estimations, we find weaker effects once we control for cluster fixed effects, especially for the effects of recent shocks.

In Table 6, focusing on the results with cluster fixed effects, we find that experiencing disaster in the most recent year has close to zero effects on enrollment between ages 5 to 8, a weakly negative association on enrollment for children between ages 9 to 12, and weakly significant effect of reducing enrollment by 1% for children ages 13 to 17. For the effects of the number of months experiencing disaster in the first 1000 days on enrollment, we find a negative age gradient as well, with a weakly positive relationship between early disaster experience and enrollment between ages 5 to 8, and strongly negative association of 0.1% reduction in enrollment for each additional early month exposed to disaster between ages 9 to 17. Results with MICS sub-national location fixed effects from column one show similar disaster effects age gradients with more sharply identified estimates.

In Table 7, we show that boys are affected more than girls by both recent and early-life disaster shocks. By interacting disaster shocks with age groups and gender, it is found that having experienced any type of disaster in most recent year is associated with higher probability of going to school for both boys and girls. It is plausible that in some setting, schools might be a safe and resourceful location for children during times of disaster 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 home more than at school, and consequently, through parental initiatives and government encouragements, locations experiencing disaster might see increased enrollment as schools become a safe refuge in times of disaster. As children age, the effects of early life disaster exposure on enrollment appears to be strongly significant negative, especially for boys. One month of additional disaster exposure in the first 1000 days of life is associated with a 0.3 percentage points reduction in

8. 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.

enrollment within boys in age 9-12, while no similar relationship 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 shock to the families, it is plausible that older children turn to drop out of school and help with housework and boys may be required to do so even earlier than girls.

In Table C.4, we find separate estimates for children in the three age groups from Pakistan, Bangladesh and other countries. In Pakistan, we find weakly negative association between recent disaster experience and enrollment in all three age groups. For early life disaster experience, we find a strongly significant negative relationship between early life disaster exposure and enrollment between ages 5 to 8, and insignificant relationships at older ages. Specifically, one month of additional disaster exposure in the first 1000 days is associated with a 0.5% reduction in enrollment between ages 5 to 8 in Pakistan. As discussed prior and shown in Figures 3 and 5, the Pakistan sample have the lowest enrollment.

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 cluster fixed effects, both recent and early disaster experiences are found to be unrelated to enrollment for children between age 9 to 12. In contrast, between ages 13 to 17, having experienced disaster in the past year is associated with a 2% reduction in enrollment, and having an additional month of early exposure reduces enrollment by 0.3%. Interestingly, in Table C.4, for children between ages 5 to 8, we find a significant positive association in Bangladesh between enrollment both recent and early shocks. This results come from the youngest cohort with disasters experiences from the most recent years.

Table C.4 also presents estimates for the other countries in the sample. Here we find negative effects of recent disaster on enrollment, especially for children between ages 9 to 12. Similar to Bangladesh, for early life disaster exposures, we find increasing negative effects of disaster on enrollment at later ages, but a positive effect for children age 5 to 8.

5.3 Numeracy skills and disaster

In Table 8, following Eq. (3), we present results from estimating the effects of child-specific life-cycle disaster histories on numeracy test scores.[9] 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 numeracy test score scales (see Figure 8 which shows the average math test score by ages, gender and countries), which varies between 0 and 54 points.

In all columns of Tables 8, we find a consistent result of weak and insignificant relationships between recent disaster on numeracy scores, but significant effects of disaster both in the first 1000 days of life as well as between the first 1000 days of life and up to the year before last year (mid-child life) on test scores. The estimates with no controls and with demographic

9. 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 numeracy scores. See Figure C.1 for the sample structure for numeracy scores, and Figure C.2 for the sample structure for reading scores.

controls suggest an impact of having disaster shock in first 1000 days of life and in mid-child life on math test scores of 0.03 and 0.02 points, respectively. Focusing on estimates from column four, we find that, averaging across children between 5 and 17 years of age and from all countries, each additional month of mid-child life disaster experience reduces test score weakly significantly by 0.018 points, and each additional month of early life disaster exposure reduces test score strongly significantly by 0.024 points. The two estimates have similar standard error, but the early life effects is 30% larger in magnitude. Estimates from column three using MICS sub-national location fixed effects show similar finding with slightly larger 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. Specifically, from column 4, we find girls have lower scores than boys. We also find the having a mother who has had any prior education increases scores, and having a mother with secondary education raises the numeracy score further. Additionally, having a mother who is alive has a weak positive effect on the test score, and the effects are stronger when the mother also resides with the child. In contrast, having a father who is alive and not living with the household weakly increases the child's test score, but having a father who is alive but living in the same household has no effects on test scores.

5.4 Heterogeneous disaster effects on numeracy skills across ages, genders, and countries

Given the substantial variations in numeracy 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 numeracy scores conditional on gender and age groups separately and jointly. Heterogeneity across country settings is shown in C.6 and C.7. Although effects of disaster shocks in recent years, mid-child life, and early life are all estimated, we only present those of mid-child life disaster experience and early-child life disaster experiences as 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 in age 7-14 are offered with the test, hence we group children based on the usual age of entering secondary school (10-12). In Table 9, we find weakly negative effects of mid and early disasters on test scores for children between age 13 to 14, the magnitudes of estimates are broadly similar to average estimates across age groups from Table 8, but the standard errors now are larger. We find generally larger and more significant negative effects of an additional month of early life disaster shock than an additional month of mid-life disaster shocks on numeracy scores across current ages. Interestingly, the estimates for effects of disaster history on children between ages 10 to 12 are close to zero for both mid- and early-life shocks.

One study on 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 shock, while girls are found to have negative impact purely on attainment measured by years of education

(De Vreyer, Guilbert, and Mesple-Somps 2015). In our results from heterogeneous analysis across genders, it is noticeable that there is a greater impact of disaster experience in ones' life cycle on boys' math test performance than girls. On average for boys in age 7 to 14, one more month with disasters in mid-child life reduces the numeracy test score by 0.03 points, while girls are not observed with such impacts (Table 10. Breaking down the heterogeneity further by gender and age groups jointly in Table 11, we find that disaster shocks in early life are associated with negative numeracy test scores for girls not only when they just start the schools but also when they are in higher grades.

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 of life at the time of disasters have negatively effected 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).

In Table C.6, we estimate heterogeneous effects by countries. We find that children in Pakistan are very strongly negatively impacted by early-life disaster shocks. however, children in Bangladesh are more impacted by mid-life disaster shock. An additional month of mid-life disaster reduces the numeracy test score by 0.05 points in Bangladesh, and an additional month of early-life disaster reduces the score by 0.07 to 0.09 points in Pakistan. Interestingly, with the break down across countries, we do not find mid-life disaster effects in Pakistan, and do not find early-life effects of disaster in Bangladesh. One important caveat for our results is that we do not capture disaster history for the same cohort of children over time. Given age compositional structure differences and disaster history differences in each country, it could be that the disaster 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 estimates of the effects of disaster on test scores in our country break-down 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 numeracy exam, there is potential 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 selection bias.

6 Conclusions

A 2023 report from United Nations Economic and Social Commission for Asia and the Pacific (UN-ESCAP) (2023, v) indicated that climate change-induced disasters pose an increasingly serious threat to Asia and the Pacific, which remains the most disaster-prone region. Disaster resilience has become an important policy concern in educational sector, where impacts on children from marginalized populations are a 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 most recent period.

Preliminary results show, overall, a significant negative effect of early life disaster exposure on enrollment and math skills, even in regional fixed effects specifications, but weaker or no corresponding effects for recent disaster exposure. There is a weak but increasingly negative relationship between recent disaster exposure and enrollment as children age. There is a more persistent negative relationship between early disaster experience and enrollment through the school-going ages. Age pattern of enrollment and learning effects of disaster exposure differ across national settings. School enrolment of children in both genders having experienced in early life any type of natural disasters is found to be affected negatively. However, although the impact on school enrolment figures is greater for boys than girls, the cognitive performance measured by MICS-administered numeracy test of girls are harder hit than the boys in older cohort (age 13-14).

Tables and Figures

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

	Survey timeframe			Sample size		Enrollment
	Year	Start-date	End-date	N	Geo-identifier‡	frac.
South Asia						
Bangladesh	2019	01/19	06/01	37925	District	0.89
Nepal	2019	05/04	11/13	7618	Region	0.93
Pakistan	2017-19	2017 12/03	2019 10/23	54072	District	0.86
East Asia						
Mongolia	2018	09/17	12/24	7277	Region	0.96
Thailand	2019	05/18	12/03	9429	Changwat	0.99
Central Asia						
Kyrgyzstan	2018	09/06	11/19	3754	Oblast	0.96
Turkmenistan	2019	05/02	08/02	3410	Region	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. † At the smallest geo-identifier available, we compute the share of enrolled in school reporting school closure due to natural disasters in the past year and s.d. across geo-identifiers. ‡ 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, attainment, progression, test scores, and school closure					
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
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
Retention in this school year t	0.15	0.36	0.00	1.00	104196
Have reading Score	0.59	0.49	0.00	1.00	87,797
Have math Score	0.90	0.30	0.00	1.00	87,797
Read score (total)	73.44	6.75	0.00	77.00	51,644
Math score (total)	14.19	7.42	0.00	54.00	78,704
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 sch 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 sch education	0.20	0.40	0.00	1.00	116768
Mother is living in same HH	0.92	0.28	0.00	1.00	144222
Father is living in same HH	0.81	0.39	0.00	1.00	144068
Panel C: Location-specific and child life-cycle-specific disaster history					
Had recent disaster (DB_A) ...					
in survey mo	0.08	0.27	0.00	1.00	144471
in this year prior survey month	0.55	0.50	0.00	1.00	144471
in year prior to 12 months ago	0.63	0.48	0.00	1.00	144471
Had disaster at least once in location-specific disaster history (DB_A) ...					
between 10 years ago until 2 years ago	0.77	0.42	0.00	1.00	144471
between 20 years ago and 10 years ago	0.77	0.42	0.00	1.00	144471
Had disaster at least once given child life-cycle-specific disaster history (DB_A) ...					
in child's first 1000 days of life (early life)	0.58	0.49	0.00	1.00	144471
between early life and 2 years before survey month (mid-child life)	0.70	0.46	0.00	1.00	144471

Note: This table shows summary statistics of all country sample on key educational outcome 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 indicator being one if there is any type of disaster in certain time span, zero if not. For example, DB_A in Survey Mo being one means there has been disaster happening in the month when the child was surveyed. In total sample, 8% of children have had any typed 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
Retention in this school year t	0.10	0.29	0.00	1.00	30,956
Math score (total)	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
Retention in this school year t	0.09	0.28	0.00	1.00	3,416
Math score (total)	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
Retention in this school year t	0.08	0.28	0.00	1.00	6,975
Math score (total)	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
Retention in this school year t	0.15	0.36	0.00	1.00	6,761
Math score (total)	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
Retention in this school year t	0.21	0.40	0.00	1.00	43,474
Math score (total)	10.31	7.66	0.00	54.00	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
Retention in this school year t	0.19	0.40	0.00	1.00	9,340
Math score (total)	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
Retention in this school year t	0.12	0.33	0.00	1.00	3,274
Math score (total)	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 indicator for current and last school year. The attainment (highest) is defined as completed years of education. Retention indicator is one if the child repeated grade in this school year compared to last school year. MICS performs reading and math test if the children are in age 7-14, the test is approved by parents or guardians and the children feel ready. We focus on math test as reading test score is provided for only 60% of children in total. In Thailand, only children up to age 14 are surveyed.

Table 4: Summary statistics for disaster experience by country

Children who had any disaster (DB_A) ...	Mean	SD	Min	Max	N
		Bangladesh			
survey mo	0.08	0.27	0.00	1.00	40,617
this year prior survey mo	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 mo	0.00	0.00	0.00	0.00	3,897
this year prior survey mo	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 mo	0.32	0.47	0.00	1.00	7,628
this year prior survey mo	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 mo	0.00	0.00	0.00	0.00	7,824
this year prior survey mo	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 mo	0.08	0.27	0.00	1.00	71,121
this year prior survey mo	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 mo	0.04	0.21	0.00	1.00	9,608
this year prior survey mo	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 being one if there is any type of disaster in certain time span, zero if not. For example, DB_A in Survey Mo being 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 disaster on enrollment

	(1)	(2)	(3)
Had disaster (DB_A) in most recent 12 months	−0.003	−0.002	−0.004
	(0.005)	(0.005)	(0.004)
# of mos. with disaster (DM_A) in first 1000 days	−0.002***	−0.002***	−0.001***
	(0.000)	(0.000)	(0.000)
Enrollment in year $t-1$	0.648***	0.641***	0.388***
	(0.003)	(0.003)	(0.005)
Attainment at start of t	0.025***	0.024***	0.012***
	(0.000)	(0.000)	(0.002)
Female		−0.015***	−0.006***
		(0.001)	(0.001)
Mother is alive		−0.015***	−0.009*
		(0.005)	(0.005)
Mother is alive × living in same HH		0.029***	0.025***
		(0.003)	(0.003)
Father is alive		0.013***	0.012***
		(0.004)	(0.003)
Father is alive × in same HH		−0.005**	−0.005**
		(0.002)	(0.002)
Mother ever educated		0.037***	0.041***
		(0.002)	(0.002)
Mother ever educated × has secondary education		0.004**	0.011***
		(0.002)	(0.002)
Observations	144354	143645	143645
Within country location FE	*Y*	*Y*	*Y*
Interview year FE	*Y*	*Y*	*Y*
Interview month FE	*Y*	*Y*	*Y*
Child age FE	*Y*	*Y*	*Y*
Enrollment t-1 × age group controls			*Y*
Attainment t × age group controls			*Y*
Enrollment t-1 × country controls			*Y*
Attainment t × country Controls			*Y*

Note: This table shows regression results corresponded with 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.

Table 6: Disaster and enrollment, heterogeneity across ages groups

	(1)	(2)
Had disaster in most recent 12 months		
× Age 5–8	0.008*	0.002
	(0.005)	(0.005)
× Age 9–12	−0.009**	−0.005
	(0.004)	(0.004)
× Age 13–17	−0.012**	−0.010*
	(0.005)	(0.005)
# of months with disaster in the first 1000 days		
× Age 5–8	0.001***	0.001*
	(0.000)	(0.000)
× Age 9–12	−0.002***	−0.001***
	(0.000)	(0.000)
× Age 13–17	−0.001***	−0.001***
	(0.000)	(0.000)
Observations	143645	143632
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 controls	Y	Y
Attainment t × age group controls	Y	Y
Enrollment t-1 × country controls	Y	Y
Attainment t × country controls	Y	Y

Note: This table shows heterogeneous analysis across ages of disaster effect on enrollment corresponded with 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.

Table 7: Disaster and enrollment, heterogeneity across gender and age groups

	(1)	(2)
Had disaster in most recent 12 months		
× Male		
× Age 5–8	0.013**	0.072**
	(0.005)	(0.030)
× Age 9–12	−0.010**	0.049
	(0.005)	(0.030)
× Age 13–17	−0.017***	0.041
	(0.006)	(0.030)
× Female		
× Age 5–8	0.003	0.064**
	(0.005)	(0.030)
× Age 9–12	−0.009*	0.051*
	(0.005)	(0.030)
× Age 13–17	−0.008	0.051*
	(0.006)	(0.030)
# of months with disasters in the first 1000 days		
× Male		
× Age 5–8	0.001**	0.001***
	(0.000)	(0.000)
× Age 9–12	−0.003***	−0.003***
	(0.000)	(0.000)
× Age 13–17	−0.001***	−0.001***
	(0.000)	(0.001)
× Female		
× Age 5–8	0.001**	0.001**
	(0.000)	(0.000)
× Age 9–12	−0.000	−0.000
	(0.000)	(0.000)
× Age 13–17	−0.001*	−0.001**
	(0.001)	(0.001)
Observations	143645	143622
Within-country location FE	*Y*	
Country × cluster FE		*Y*
Interview year FE	*Y*	*Y*
Interview month FE	*Y*	*Y*
Child age FE	*Y*	*Y*
Enrollment t-1 × age group controls	*Y*	*Y*
Attainment t × age group controls	*Y*	*Y*
Enrollment t-1 × country controls	*Y*	*Y*
Attainment t × country controls	*Y*	*Y*

Note: This table shows heterogeneous analysis across countries and ages of disaster effect on enrollment. This is corre-sponded with 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.

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

	(1)	(2)	(3)	(4)
***Recent** disaster experience:*				
had disaster in most recent 12 months	-0.126	0.258	-0.059	0.350
	(0.129)	(0.714)	(0.128)	(0.704)
# of disaster mos. year before last year	-0.011	-0.055	-0.038	-0.107
	(0.080)	(0.238)	(0.079)	(0.240)
***Mid-child life** disaster experience, # of disaster months:*				
(> 1000 days) & (< yr. before last yr.)	-0.029^{***}	-0.022^{**}	-0.019^{*}	-0.018^{*}
	(0.010)	(0.010)	(0.010)	(0.010)
***Early life** disaster experience, # of disaster months:*				
in the first 1000 days	-0.037^{***}	-0.030^{***}	-0.028^{***}	-0.024^{**}
	(0.010)	(0.010)	(0.010)	(0.010)
Female			-0.401^{***}	-0.400^{***}
			(0.036)	(0.037)
Mother is alive			0.312^{**}	0.201
			(0.158)	(0.162)
Mother is alive × living in same HH			0.064	0.146^{*}
			(0.075)	(0.079)
Father is alive			0.246^{**}	0.155
			(0.101)	(0.106)
Father is alive × living in same HH			-0.235^{***}	-0.205^{***}
			(0.057)	(0.060)
Mother ever educated			1.345^{***}	0.980^{***}
			(0.054)	(0.058)
Mother ever educated × has secondary			0.991^{***}	0.813^{***}
			(0.044)	(0.048)
Observations	78657	78502	78305	78141
Within country location FE	*Y*		*Y*	
Country X 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*
Country X Attainment t FE	*Y*	*Y*	*Y*	*Y*

Note: This table shows regression results of math test score and disaster shock. This is corresponded with 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 score across ages and countries is shown in Figure 8.

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

	(1)	(2)
# of months with disaster in mid-child life		
× Age 7–9	−0.006	0.003
	(0.016)	(0.017)
× Age 10–12	−0.005	0.002
	(0.015)	(0.016)
× Age 13–14	−0.009	−0.002
	(0.014)	(0.015)
# of months with disaster in the first 1000 days		
× Age 7–9	−0.035**	−0.022
	(0.017)	(0.018)
× Age 10–12	0.016	0.012
	(0.015)	(0.015)
× Age 13–14	−0.020	−0.016
	(0.017)	(0.018)
Observations	78303	78139
Within country location FE	*Y*	
Country X cluster FE		*Y*
Interview year FE	*Y*	*Y*
Interview month FE	*Y*	*Y*
Child age FE	*Y*	*Y*
Country X Attainment t FE	*Y*	*Y*

Note: This table shows heterogeneous analysis across ages of disaster effect on math test score. This is corresponded with Equation 3 with interaction 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.

Table 10: Disaster and math test score, heterogeneity across gender

	(1)	(2)
# of months with disasters in mid-child life		
× Male	-0.030^{***}	-0.029^{***}
	(0.010)	(0.010)
× Female	-0.009	-0.008
	(0.010)	(0.010)
# of months with disasters in first 1000 days of life		
× Male	-0.024^{**}	-0.025^{**}
	(0.012)	(0.012)
× Female	-0.032^{***}	-0.025^{**}
	(0.012)	(0.012)
Observations	78305	78141
Within country location FE	*Y*	
Country X cluster FE		*Y*
Interview year FE	*Y*	*Y*
Interview month FE	*Y*	*Y*
Child age FE	*Y*	*Y*
Country X Attainment t FE	*Y*	*Y*

Note: This table shows heterogeneous analysis across gender of disaster effect on math test score. This is corresponded with Equation 3 with interaction 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.

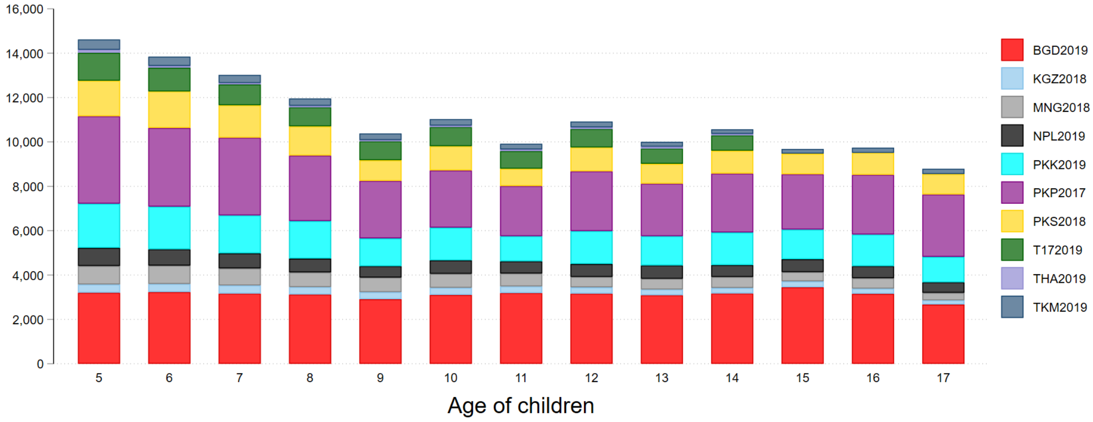
Table 11: Disaster and math test scores, heterogeneity across gender and ages groups

	(1)	(2)
# of months with disaster after 1000 days of life until 2 yr before survey month		
× Male		
× Age 7 to 9	−0.022	−0.014
	(0.017)	(0.017)
× Age 10 to 12	−0.013	−0.006
	(0.015)	(0.016)
× Age 13 to 14	−0.019	−0.010
	(0.015)	(0.015)
× Female		
× Age 7 to 9	0.009	0.018
	(0.017)	(0.017)
× Age 10 to 12	0.003	0.009
	(0.015)	(0.016)
× Age 13 to 14	−0.000	0.005
	(0.014)	(0.015)
# of months with disaster in the first 1000 days of life		
× Male		
× Age 7 to 9	−0.032*	−0.023
	(0.020)	(0.020)
× Age 10 to 12	0.013	0.018
	(0.018)	(0.019)
× Age 13 to 14	0.005	−0.005
	(0.020)	(0.022)
× Female		
× Age 7 to 9	−0.039**	−0.021
	(0.019)	(0.020)
× Age 10 to 12	0.018	0.005
	(0.018)	(0.019)
× Age 13 to 14	−0.044**	−0.025
	(0.021)	(0.022)
Observations	78305	78141
Within country location FE	*Y*	
Country X cluster FE		*Y*
Interview year FE	*Y*	*Y*
Interview month FE	*Y*	*Y*
Child age FE	*Y*	*Y*
Country X Attainment t FE	*Y*	*Y*

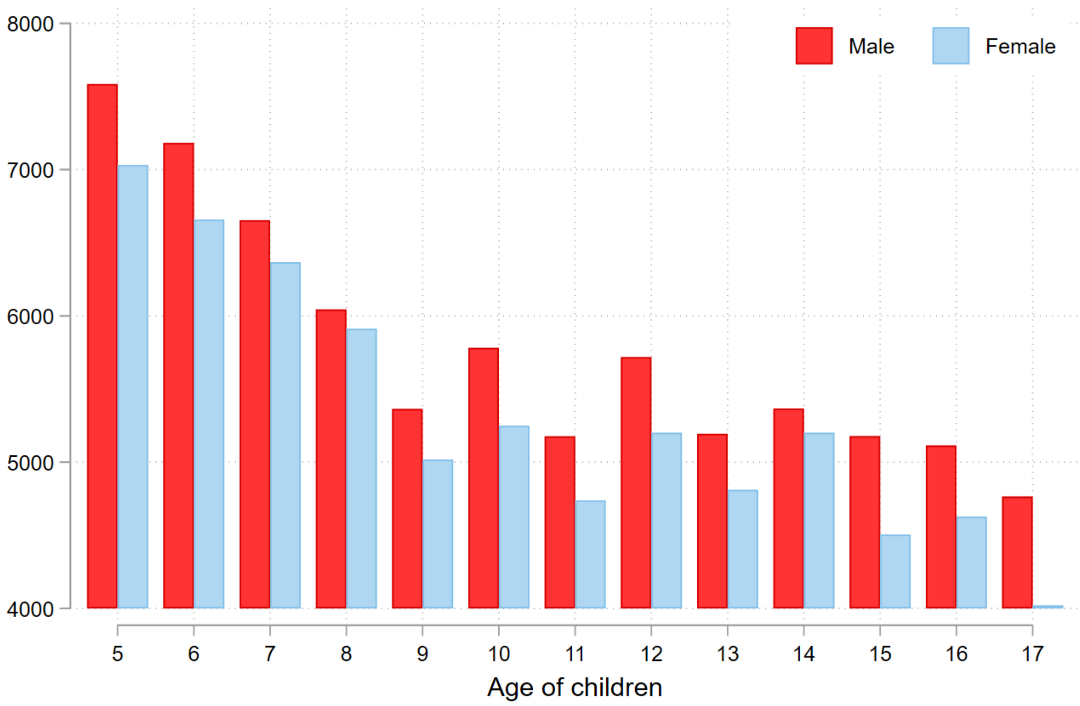
Note: This table shows heterogeneous analysis across gender and ages of disaster effect on math test scores. This is corresponded with Equation 3 with interacting disaster shocks between age groups and gender. The first 1000 days of life is defined as the period from conception to 24 months of age in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

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

(a) Sample Size Across Countries and Ages



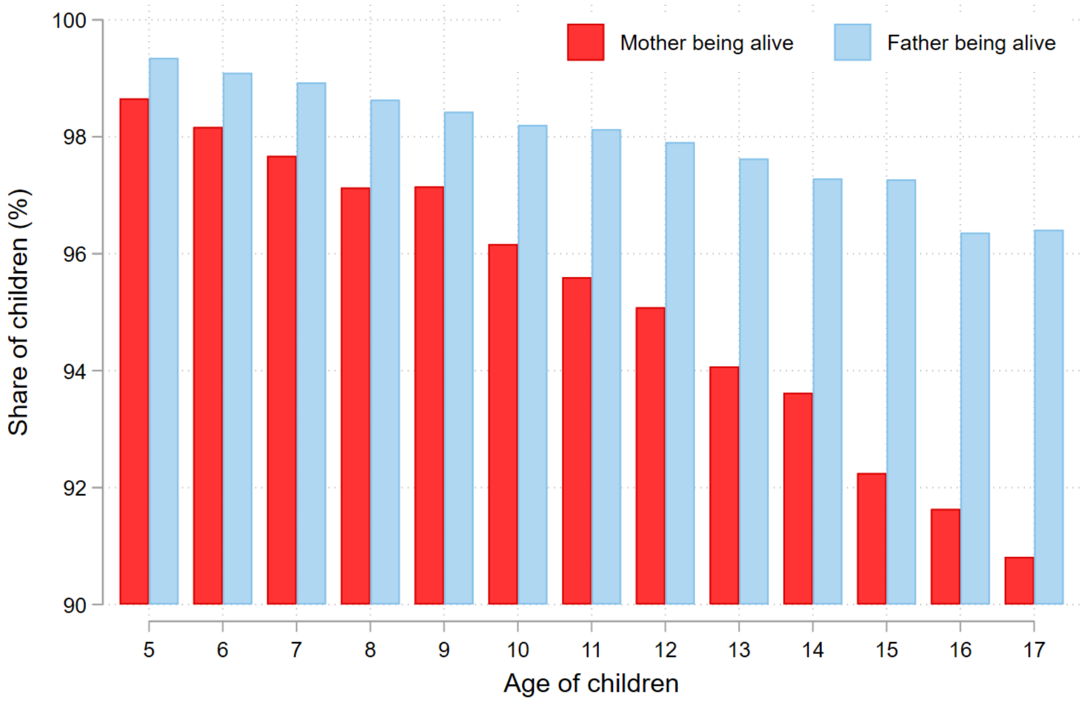
(b) Sample Size Across Gender and Ages



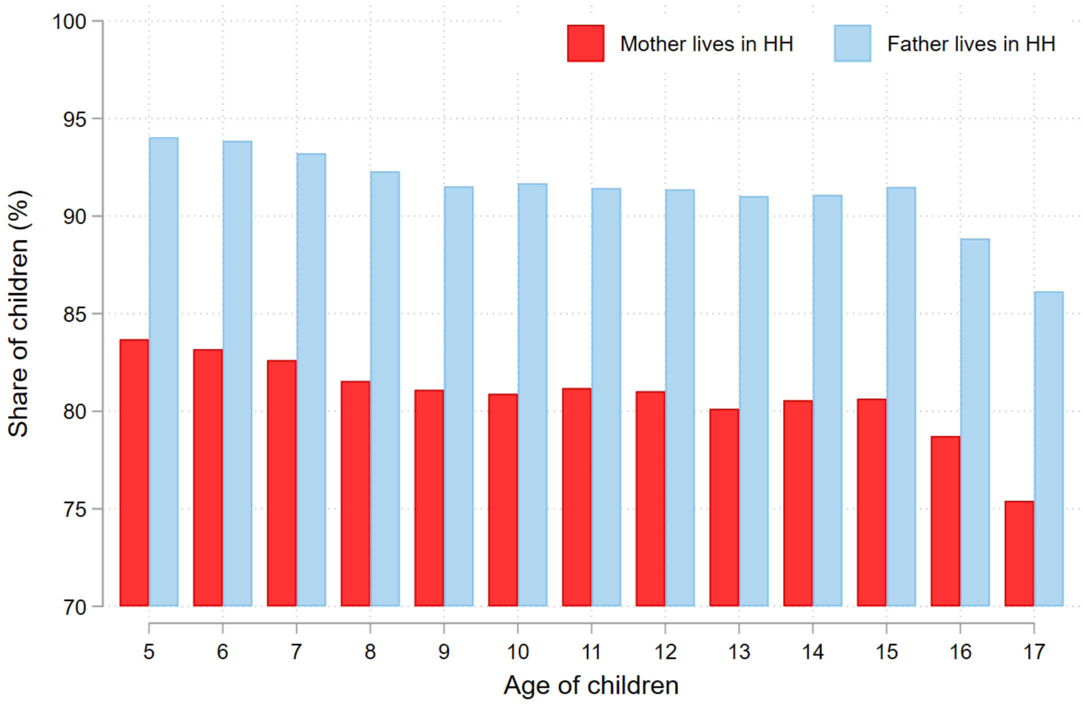
Note: Panel (a) shows number of children in each age and country. There are 144,471 children in full sample dominated by Bangladesh and Pakistan. Geographically, within all Asian countries covered in MICS6, we focus on low- and middle-income countries whose data is collected pre-pandemic. For every age 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 Age

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



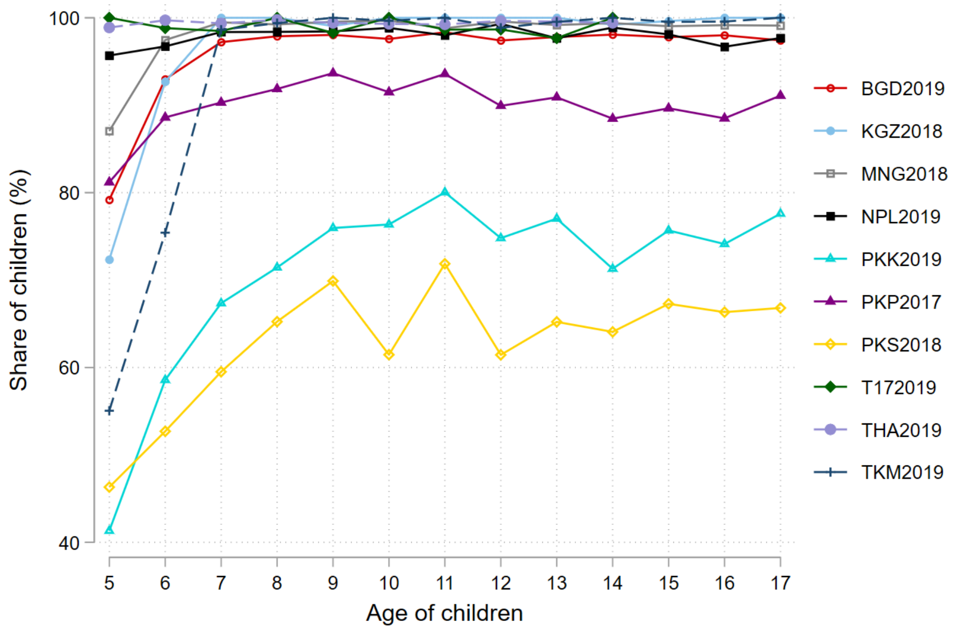
(b) Share of Parents Living with Mother or Father by Ages



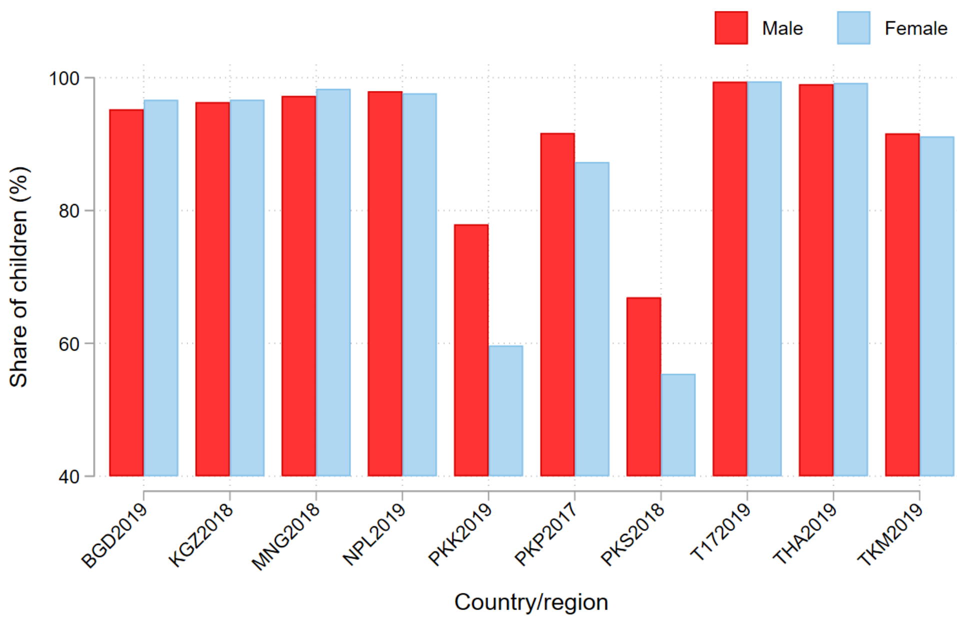
Note: Panel (a) shows the share of children with mother or father who is alive by child ages. Panel (b) shows the share of children living with either mother or father by ages. Blue (orange) bars represent shares of fathers (mothers).

Figure 3: Share of Children Ever-enrolled

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



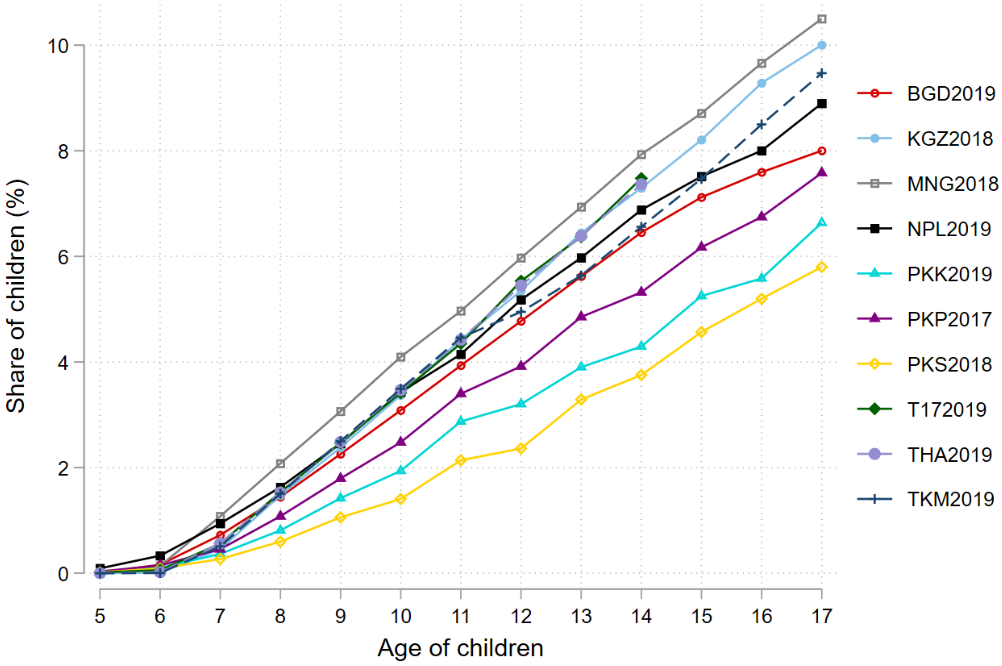
(b) Share of Children Ever Enrolled in Any Education Program of School by Gender and Countries



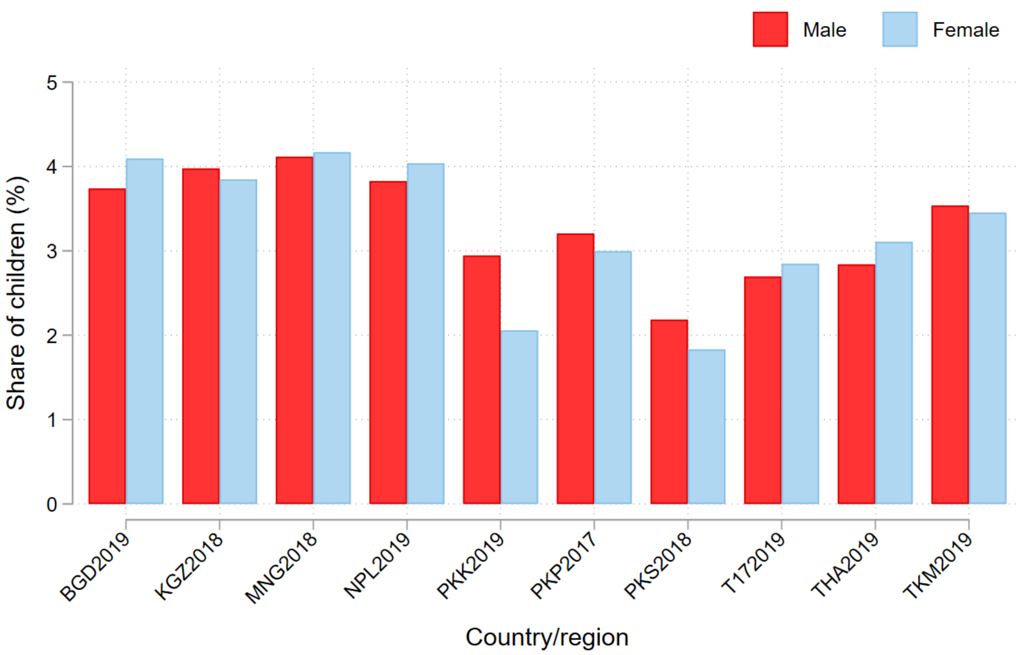
Note: The survey asks if a child has ever been enrolled in school. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged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

Figure 4: Average Highest Grade Completed by Age and Country

(a) Average of Highest Grade Completed by Ages and Countries



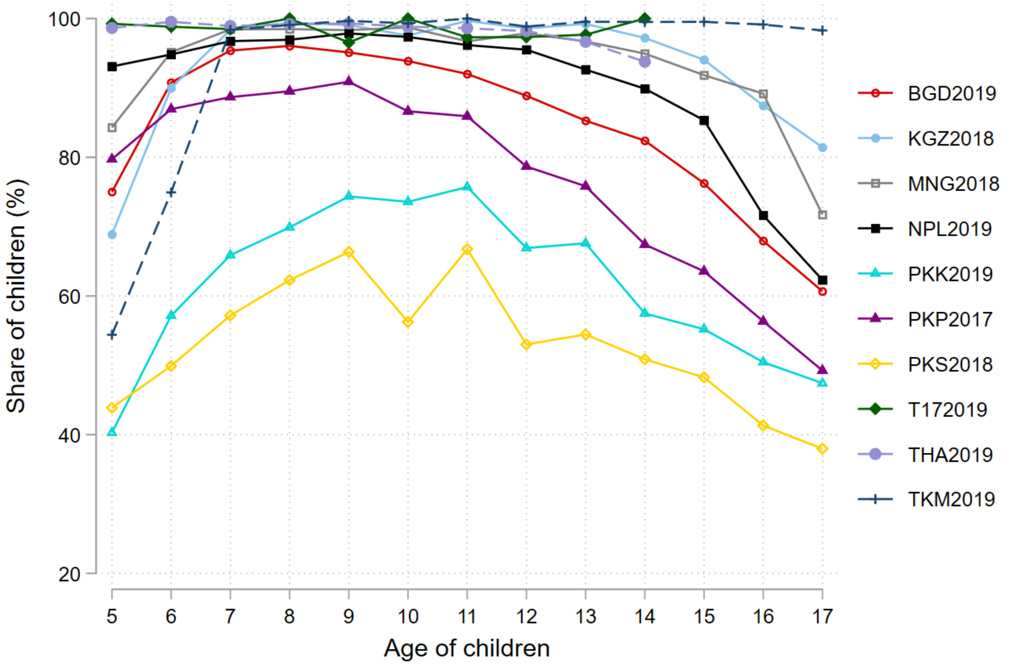
(b) Average of Highest Grade Completed by Gender and Countries (All Available Ages)



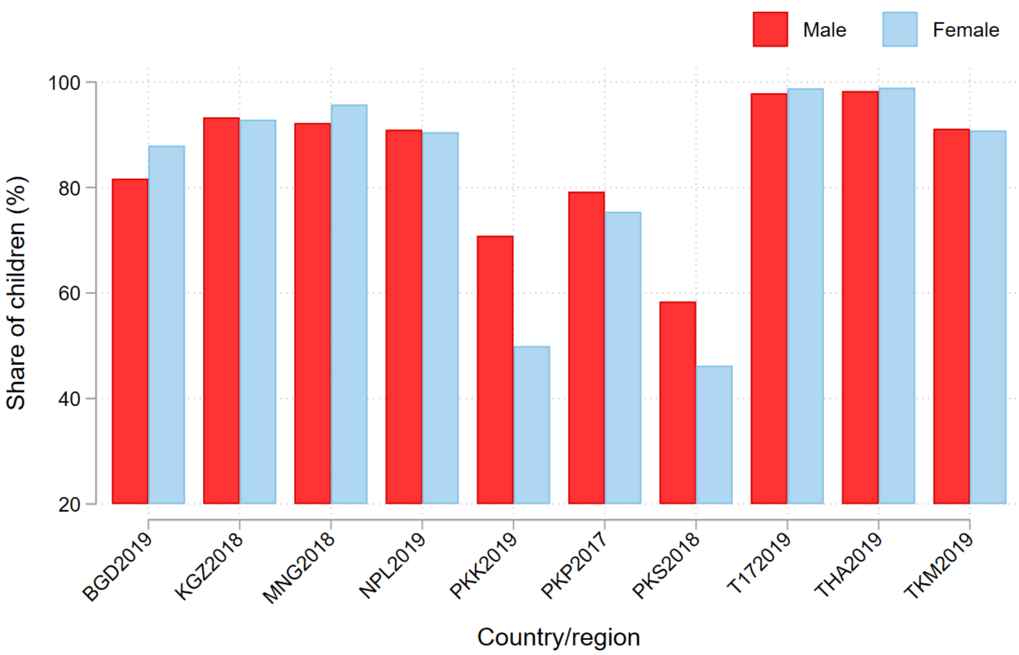
Note: Gender indicator is 0 for male and 1 for female. In Thailand, data is observed only up to age 14, in all other countries, data is available up to age 17. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **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 5: Enrollment Rate This Year

(a) Enrollment Rate in This Year by Ages and Countries



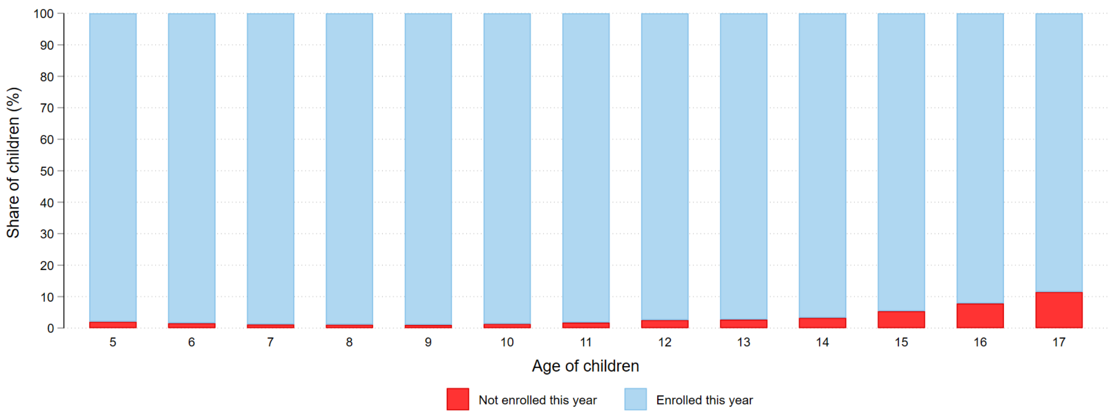
(b) Enrollment Rate in This Year by Gender and Countries



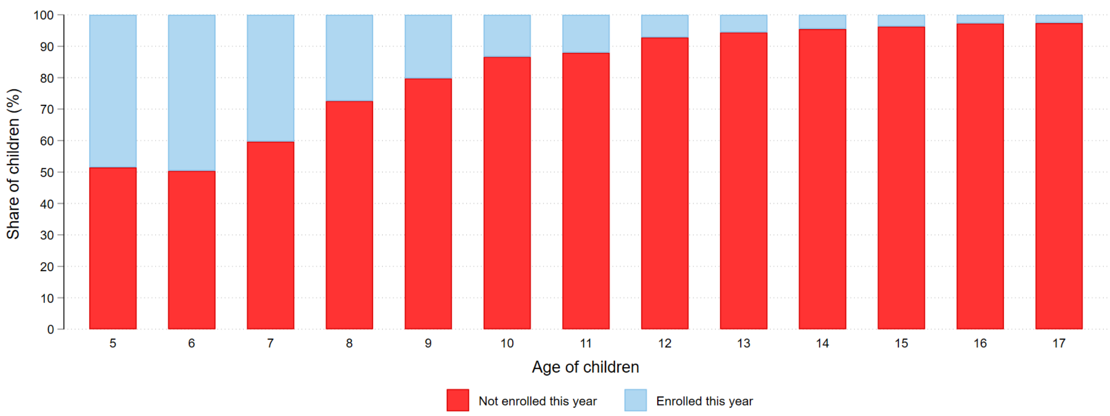
Note: Enrollment rate in the current year. In Thailand, data is observed only up to age 14, in all other countries, data is available up to age 17. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** 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 6: Enrollment Transition Probabilities By Ages

(a) Enrollment Rate in This Year Conditional on **Enrolled** Last Year



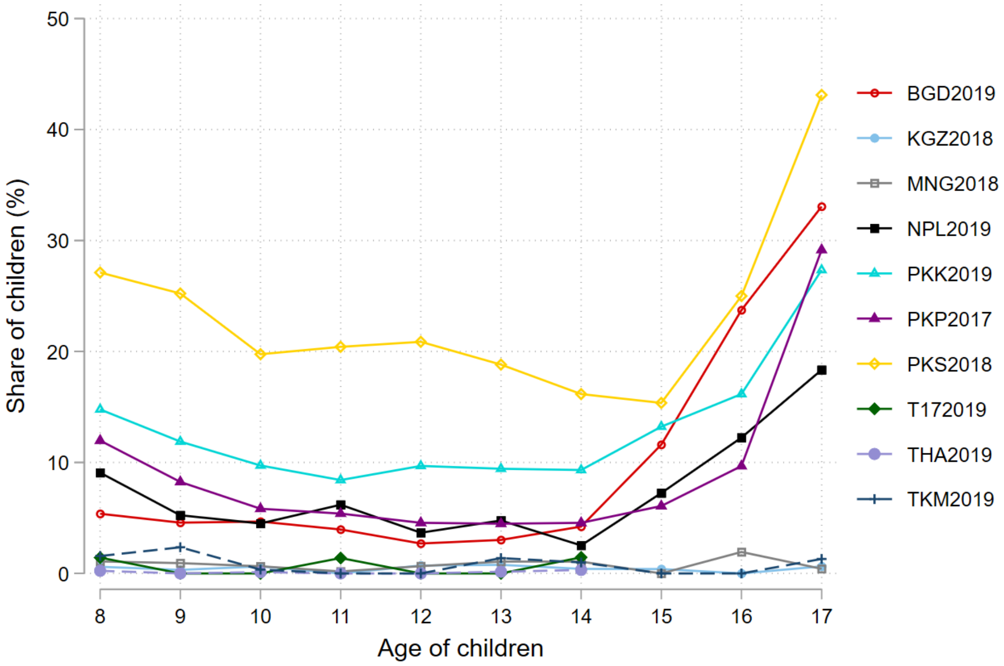
(b) Enrollment Rate in This Year Conditional on **Not** Enrolled Last Year



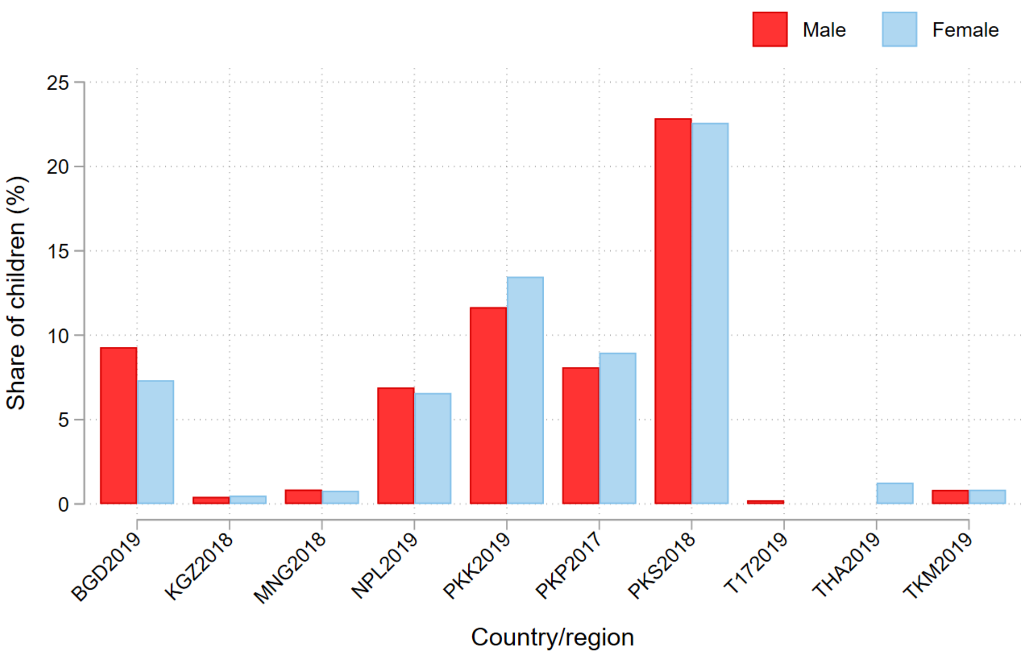
Note: Enrollment rate in the current year conditional on enrollment rate last year. The results shows conditional probabilities. Share of children who were enrolled in the year prior to the survey and continued to enroll in the survey year is greater than 95% up to age 14, but falls to 88% by age 17. Share of children who come back to enrollment after not enrolled in the last year before the survey decreases with age and falls below 10% after age 11.

Figure 7: Retention (Grade Repetition) By Age and Country

(a) Retention Rate by Ages and Countries



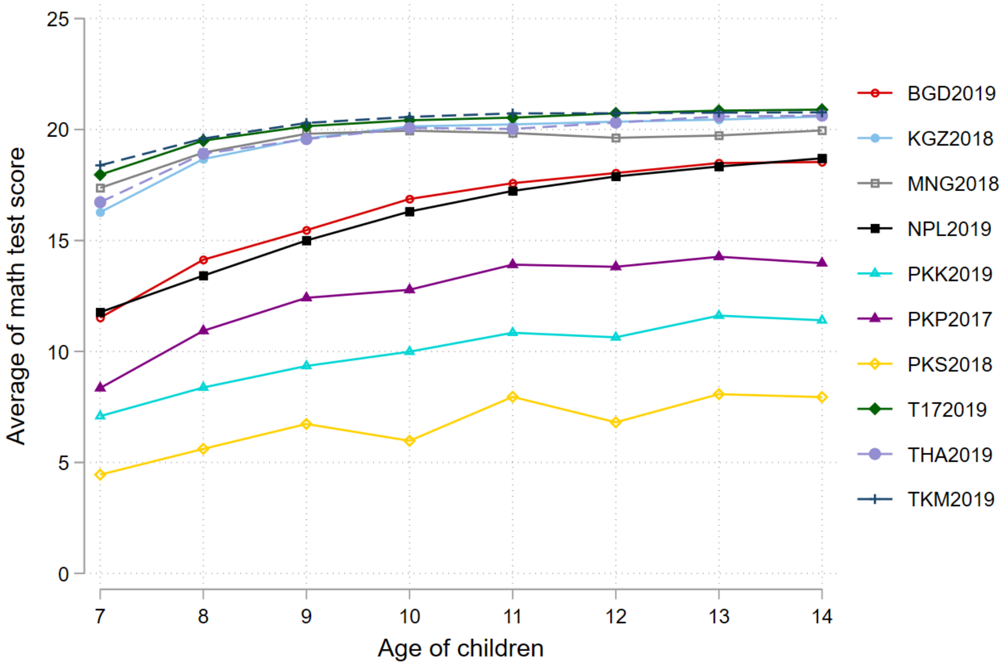
(b) Retention Rate by Gender and Countries ($\geq$ Age 8)



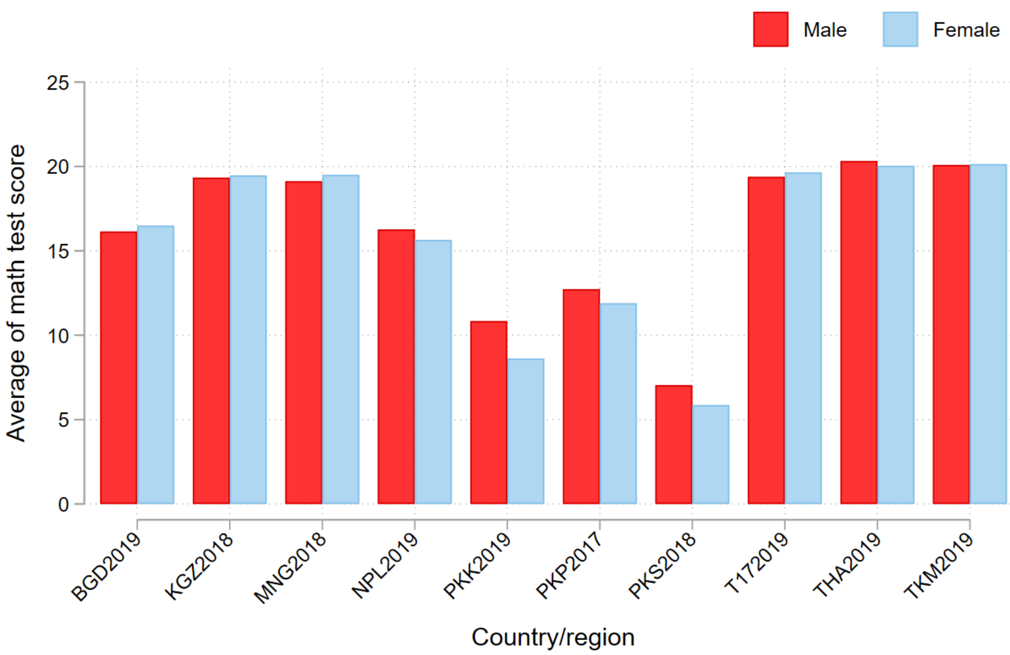
Note: If a child reports attending the same grade this and last year, a child is repeating a grade and experiencing grade retention. Gender indicator is 0 for male and 1 for female. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa,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

Figure 8: Distribution on Numeracy/Math Test Score

(a) Math Test Score Across Ages and Countries

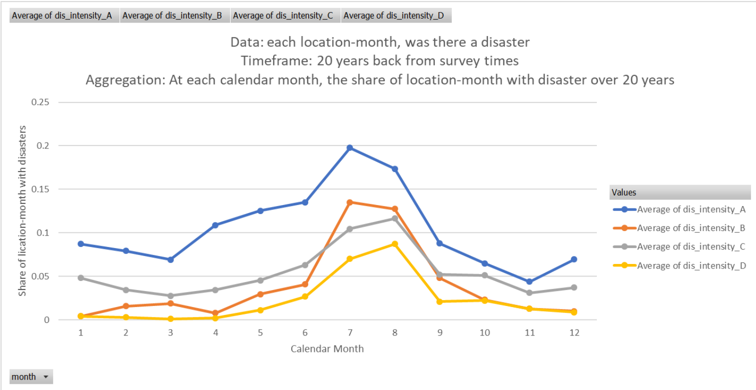


(b) Math Test Score by Gender and Countries (Age 7-14)

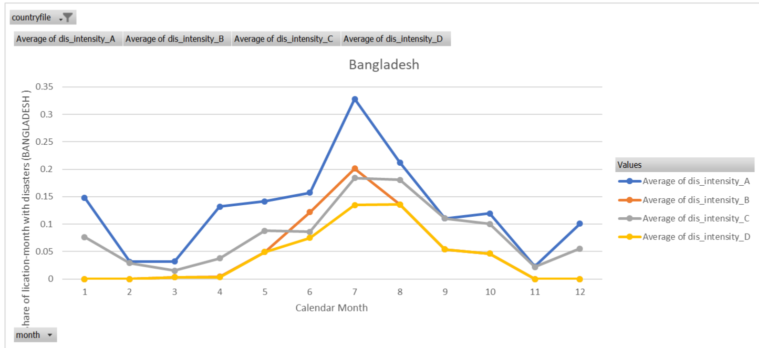


Note: Gender indicator is 0 for male and 1 for female. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP** for Punjab, **PKS** for Sindh), Mongolia (2018, **MNG**), Thailand (2019, **T17** for 17 disadvantaged Thai provinces, **THA** Bangkok only)), and Kyrgyzstan (2018, **KGZ**), and Turkmenistan (2019, **KGZ**).

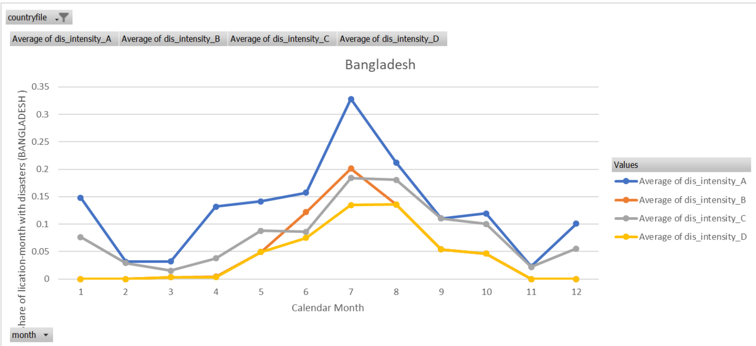
Figure 9: Share of Location-month that Experience Disaster Shock in Each Calendar Month over 20 Years



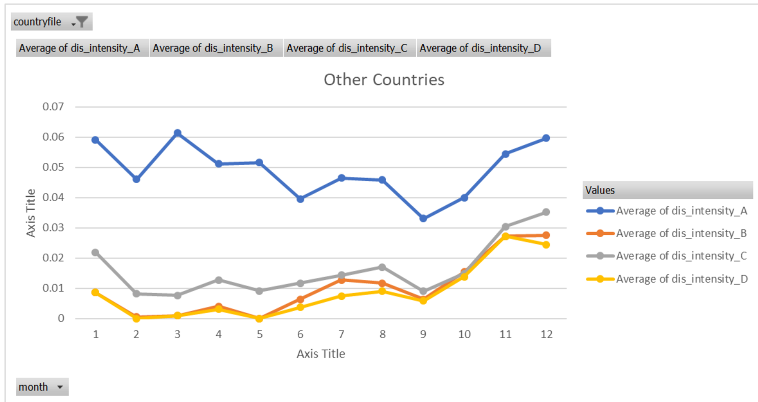
(a) All Countries



(b) Bangladesh Only



(c) Pakistan Only



(d) Other Countries

Note: For each location in every month from latest survey month to 20 years ago, we construct disaster indicator with the Em-Dat Data. For all locations in past 20 years, share of location-month with disaster shock of each type is shown cross calendar month of the year. This shows that For all types, during summer the locations are hit by disaster for any type most. This also shows focusing only on one category of disaster shocks omits large proportion of overall shocks.

References

Alam, Shamma Adeeb. 2015. "Parental Health Shocks, Child Labor and Educational Outcomes: Evidence from Tanzania." *Journal of health economics* 44:161–175.

Alban Conto, Carolina, Spogmai Akseer, Thomas Dreesen, Akito Kamei, Suguru Mizunoya, and Annika Rigole. 2021. "Potential Effects of COVID-19 School Closures on Foundational Skills and Country Responses for Mitigating Learning Loss." *International Journal of Educational Development* 87 (November 1, 2021): 102434. https://doi.org/10.1016/j.ijedudev.2021.102434. https://www.sciencedirect.com/science/article/pii/S0738059321000870.

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

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

Amouzou, Agbessi, Vrinda Mehra, Liliana Carvajal–Aguirre, Shane M. Khan, Deborah Sitrin, and Lara ME Vaz. 2017. "Measuring Postnatal Care Contacts for Mothers and Newborns: An Analysis of Data from the MICS and DHS Surveys." *Journal of Global Health* 7, no. 2 (December 20, 2017): 020502. https://doi.org/10.7189/jogh.07.020502. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5804502/.

Andrabi, Tahir, Benjamin Daniels, and Jishnu Das. 2021. "Human Capital Accumulation and Disasters: Evidence from the Pakistan Earthquake of 2005." *Journal of Human Resources* (June). https://doi.org/10.3368/jhr.59.2.0520-10887R1. https://jhr.uwpress.org/content/early/2021/06/02/jhr.59.2.0520-10887R1.

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

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

Bain, Rob, Rick Johnston, Shane Khan, Attila Hancioglu, and Tom Slaymaker. 2020. *Monitoring Drinking Water Quality in Nationally Representative Household Surveys: Cross-Sectional Analysis of 20 Multiple Indicator Cluster Surveys 2014-2019,* September 23, 2020. https://doi.org/10.1101/2020.09.21.20174862. https://www.medrxiv.org/content/10.1101/2020.09.21.20174862v1.

Bandara, Amarakoon, Rajeev Dehejia, and Shaheen Lavie-Rouse. 2015. "The Impact of Income and Non-Income Shocks on Child Labor: Evidence from a Panel Survey of Tanzania." *World development* 67:218–237.

Botzen, WJ Wouter, Olivier Deschenes, and Mark Sanders. 2019. "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies." *Review of Environmental Economics and Policy.*

Boustan, Leah Platt, Matthew E Kahn, Paul W Rhode, and Maria Lucia Yanguas. 2020. "The Effect of Natural Disasters on Economic Activity in Us Counties: A Century of Data." *Journal of Urban Economics* 118:103257.

Casco, José L. 2022. "Household Choices of Child Activities in the Presence of Cash Transfers." *Journal of Economic Behavior & Organization* 196 (April 1, 2022): 524–545. https://doi.org/10.1016/j.jebo.2022.02.017. https://www.sciencedirect.com/science/article/pii/S0167268122000634.

Case, Anne, and Christina Paxson. 2010. "Causes and Consequences of Early-Life Health." *Demography* 47:S65–S85.

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

Charil, Arnaud, David P Laplante, Cathy Vaillancourt, and Suzanne King. 2010. "Prenatal Stress and Brain Development." *Brain research reviews* 65 (1): 56–79.

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

Ciraudo, Martha. 2020. "The Relationship Between Prenatal Stress Due to Natural Disasters and the Long-Term Educational Achievement of Chilean Students." ALM, Harvard University. https://www.proquest.com/docview/2480641324/abstract/C4B5A0AD63C24687PQ/1.

Currie, Janet, and Maya Rossin-Slater. 2013. "Weathering the Storm: Hurricanes and Birth Outcomes." *Journal of Health Economics* 32, no. 3 (May): 487–503. https://doi.org/10.1016/j.jhealeco.2013.01.004. https://www.sciencedirect.com/science/article/pii/S0167629613000052.

Cutter, Susan L., Bryan J. Boruff, and W. Lynn Shirley. 2003. "Social Vulnerability to Environmental Hazards*." *Social Science Quarterly* 84 (2): 242–261. https://doi.org/10.1111/1540-6237.8402002. https://onlinelibrary.wiley.com/doi/abs/10.1111/1540-6237.8402002.

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

Eilerts, Hallie, Julio Romero Prieto, Jeffrey W. Eaton, and Georges Reniers. 2021. "Age Patterns of Under-5 Mortality in Sub-Saharan Africa During 1990–2018: A Comparison of Estimates from Demographic Surveillance with Full Birth Histories and the Historic Record." *Demographic research* 44:415–442. https://doi.org/10.4054/demres.2021.44.18. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8974662/.

Emerson, Eric, and Gwynnyth Llewellyn. 2022. "The Association Between Household Wealth and the Prevalence of Child Disability and Specific Functional Limitations: Analysis of Nationally Representative Cross-Sectional Surveys in 40 Low-and Middle-Income Countries." *Disability and Health Journal* 15 (4): 101364.

Felbermayr, Gabriel, and Jasmin Gröschl. 2014. "Naturally Negative: The Growth Effects of Natural Disasters." *Journal of development economics* 111:92–106.

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

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

Glewwe, Paul, Hanan G Jacoby, and Elizabeth M King. 2001. "Early Childhood Nutrition and Academic Achievement: A Longitudinal Analysis." *Journal of public economics* 81 (3): 345–368.

Glewwe, Paul, and Elizabeth M King. 2001. "The Impact of Early Childhood Nutritional Status on Cognitive Development: Does the Timing of Malnutrition Matter?" *The world bank economic review* 15 (1): 81–113.

Gottlieb, Carissa A, Matthew J Maenner, Claudia Cappa, and Maureen S Durkin. 2009. "Child Disability Screening, Nutrition, and Early Learning in 18 Countries with Low and Middle Incomes: Data from the Third Round of UNICEF's Multiple Indicator Cluster Survey (2005–06)." *The Lancet* 374, no. 9704 (November 28, 2009): 1831–1839. https://doi.org/10.1016/S0140-6736(09)61871-7. https://www.sciencedirect.com/science/article/pii/S0140673609618717.

Guarcello, Lorenzo, Fabrizia Mealli, and Furio Camillo Rosati. 2010. "Household Vulnerability and Child Labor: The Effect of Shocks, Credit Rationing, and Insurance." *Journal of population economics* 23:169–198.

Guha-Sapir, D., R. Below, and Ph. Hoyois. 2023. *EM-DAT: The CRED/OFDA International Disaster Database - Université Catholique De Louvain – Brussels – Belgium.* www.emdat.be.

———. *EM-DAT: The CRED/OFDA International Disaster Database - Université Catholique De Louvain – Brussels – Belgium.* www.emdat.be.

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

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

Ipcc, Intergovernmental Panel on Climate Change. 2022. *Global Warming of 1.5°c: IPCC Special Report on Impacts of Global Warming of 1.5°c Above Pre-Industrial Levels in Context of Strengthening Response to Climate Change, Sustainable Development, and Efforts to Eradicate Poverty.* 1st ed. Cambridge University Press, June 9, 2022. https://doi.org/10.

1017/9781009157940. https://www.cambridge.org/core/product/identifier/9781009157940/type/book.

Kahn, Matthew E. 2005. "The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions." *Review of economics and statistics* 87 (2): 271–284.

King, Suzanne, and David P Laplante. 2005. "The Effects of Prenatal Maternal Stress on Children's Cognitive Development: Project Ice Storm." *Stress* 8 (1): 35–45.

Klomp, Jeroen, and Kay Valckx. 2014. "Natural Disasters and Economic Growth: A Meta-Analysis." *Global Environmental Change* 26:183–195.

Lazzaroni, Sara, and Peter AG van Bergeijk. 2014. "Natural Disasters' Impact, Factors of Resilience and Development: A Meta-Analysis of the Macroeconomic Literature." *Ecological Economics* 107:333–346.

Leiter, Andrea M, Harald Oberhofer, and Paul A Raschky. 2009. "Creative Disasters? Flooding Effects on Capital, Labour and Productivity Within European Firms." *Environmental and Resource Economics* 43:333–350.

Lin, Ming-Jen, and Elaine M. Liu. 2014. "Does in Utero Exposure to Illness Matter? The 1918 Influenza Epidemic in Taiwan as a Natural Experiment." *Journal of Health Economics* 37 (September): 152–163. https://doi.org/10.1016/j.jhealeco.2014.05.004. https://www.sciencedirect.com/science/article/pii/S0167629614000678.

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

———. 2022b. "The Impact of a Natural Disaster on the Incidence of Fetal Losses and Pregnancy Outcomes." *Working Paper.*

Mavhura, Emmanuel, and Komal Raj Aryal. 2023. "Disaster Mortalities and the Sendai Framework Target a: Insights from Zimbabwe." *World Development* 165:106196.

MICS6. *UNICEF, MICS6.* https://mics.unicef.org/surveys.

Mizunoya, Suguru, and Diogo Amaro. 2020. *A Statistical Data Analysis Manual Using Multiple Indicator Cluster Surveys (MICS6) with a Special Focus on Achieving the Sustainable Development Goals.* December.

Noy, Ilan. 2009. "The Macroeconomic Consequences of Disasters." *Journal of Development economics* 88 (2): 221–231.

Olsson, Lennart, Maggie Opondo, Petra Tschakert, Arun Agrawal, Siri Eriksen, Shiming Ma, Leisha Perch, et al. 2014. "Livelihoods and Poverty." In *Climate Change 2014: Impacts, Adaptation, and Vulnerability,* edited by C.B. Field, V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, et al., 793–832. Cambridge University Press. https://portal.research.lu.se/en/publications/livelihoods-and-poverty-climate-change-2014-impacts-adaptation-an.

Opper, Isaac M, R Jisung Park, and Lucas Husted. 2023. "The Effect of Natural Disasters on Human Capital in the United States." *Nature human behaviour,* 1–12.

Panwar, Vikrant, and Subir Sen. 2020. "Disaster Damage Records of Em-Dat and Desinventar: A Systematic Comparison." *Economics of disasters and climate change* 4 (2): 295–317.

Rondó, Patricia HC, Rodrigo Fernando Ferreira, Fabio Nogueira, Maria CN Ribeiro, Herman Lobert, and Rinaldo Artes. 2003. "Maternal Psychological Stress and Distress as Predictors of Low Birth Weight, Prematurity and Intrauterine Growth Retardation." *European journal of clinical nutrition* 57 (2): 266–272.

Sable, Marjorie R, and Deborah Schild Wilkinson. 2000. "Impact of Perceived Stress, Major Life Events and Pregnancy Attitudes on Low Birth Weight." *Family planning perspectives,* 288–294.

Siddiqui, Tasneem. 2015. *National Strategy on the Management of Disaster and Climate Induced Internal Displacement (NSMDCIID).* Technical report.

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

Skidmore, Mark, and Hideki Toya. 2002. "Do Natural Disasters Promote Long-Run Growth?" *Economic inquiry* 40 (4): 664–687.

Stocker, Thomas. 2014. *Climate Change 2013: The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press, March 24, 2014.

Sy, Bocar, Corine Frischknecht, Hy Dao, David Consuegra, and Gregory Giuliani. 2019. "Flood Hazard Assessment and the Role of Citizen Science." *Journal of Flood Risk Management* 12 (S2): e12519.

Tian, Xinping, Jinquan Gong, and Zhe Zhai. 2022. "Natural Disasters and Human Capital Accumulation: Evidence from the 1976 Tangshan Earthquake." *Economics of Education Review* 90 (October 1, 2022): 102304. https://doi.org/10.1016/j.econedurev.2022.102304. https://www.sciencedirect.com/science/article/pii/S0272775722000772.

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

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

Torche, Florencia. 2011. "The Effect of Maternal Stress on Birth Outcomes: Exploiting a Natural Experiment." *Demography* 48 (4): 1473–1491.

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

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

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

United Nations. 2021. *Climate and Weather Related Disasters Surge Five-Fold Over 50 Years, but Early Warnings Save Lives.* UN News: Global perspective, human stories, September. https://news.un.org/en/story/2021/09/1098662.

United Nations Economic and Social Commission for Asia and the Pacific (UN-ESCAP). 2023. *Seizing the Moment: Targeting Transformative Disaster Risk Resilience.* Flagship ST/ESCAP/3093. Bangkok: UN.ESCAP. https://repository.unescap.org/handle/20.500.12870/6258.

Weinstock, Marta. 2005. "The Potential Influence of Maternal Stress Hormones on Development and Mental Health of the Offspring." *Brain, behavior, and immunity* 19 (4): 296–308.

Zahran, Sammy, Samuel D. Brody, Walter Gillis Peacock, Arnold Vedlitz, and Himanshu Grover. 2008. "Social Vulnerability and the Natural and Built Environment: A Model of Flood Casualties in Texas." *Disasters* 32 (4): 537–560. https://doi.org/10.1111/j.1467-7717.2008.01054.x. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-7717.2008.01054.x.

ONLINE APPENDIX

Are 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)

This is the MICS data appendix.

A.1 Data Description

We use the 6th round of the Multiple Indicator Cluster Survey (MICS6) to study the educational outcomes effect of natural disasters. MICS is a global multi-purpose survey program conducted by the United Nations Children's Fund (UNICEF), and it provides statistically sound and internationally comparable data on the situation of children and women. From mid-1990s until now, 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.

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 unit of analysis is household and individual. 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 the 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 is a densely populated, low-lying country with substantial exposure to cyclones, floods and drought

A.1. For example, MICS6 for Viet Nam started in 2020 until 2021, and excluded in this project 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" (**empty citation**) (Comprehensive Disaster Management Programme (2015). National Strategy on the Management of Disaster and Climate Induced Internal Displacement, Dhaka: Ministry of Disaster Management and Relief.).

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?

CB9 (ED15). At any time during the previous school year did (name) attend school or any early childhood education programme?

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.

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_enrollasty* 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_enrolthisy* 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 repsonse" 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 textitedu_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 otherwise. 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

We consider children age and gender as the most important 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 is alive. If she is alive, the question moves on to if she is living in the same household and where she live in if not. Same structure is applied to father. We construct the indicator for motherless or fatherless, and the joint distribution of both indicators show the overall parental loss. Child living with mother indicator is one if the child is living with her mother and zero if not, which means if the mother is not alive, rather than skipping this indicator, we treat it as zero. Figures 2 present the marginal distribution as well the the joint distribution for parental loss and cohabitation.

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

This is the climate data (EM-DAT) appendix.

B.1 Data Description

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. It 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). Entries in the EM-DAT/CRED database are based on any of the following: (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 researchers to link them with other databases such as Dartmouth Flood Observatory, Global Volcanism Program, and USGS.

Choosing type of disaster, countries, and time period, the raw data can be downloaded as an Excel Worksheet. In this raw file, each row is one disaster and columns are information associated with this one single 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.

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: Regression of Enrollment t on Disaster Using Different Recent Shock Measures

	(1)	(2)	(3)	(4)	(5)
DB_A in Survey Mo	0.006				
	(0.004)				
DB_A in Most Recent 3 Mo		0.003			
		(0.004)			
DB_A in Most Recent 12 Mo			−0.004		
			(0.004)		
DM_A in Most Recent 12 Mo				0.003	
				(0.003)	
School Closure Rate in Location					−0.004
					(0.013)
DM_A in First 1000 Days of Life	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Enrollment in t-1	0.388^{***}	0.388^{***}	0.388^{***}	0.388^{***}	0.388^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Attainment at start of t	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother is alive	-0.009^{*}	-0.009^{*}	-0.009^{*}	-0.009^{*}	-0.009^{*}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Father is alive	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mother is living in same HH	0.025^{***}	0.025^{***}	0.025^{***}	0.025^{***}	0.025^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Father is living in same HH	-0.005^{**}	-0.005^{**}	-0.005^{**}	-0.005^{**}	-0.005^{**}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mother ever educated	0.041^{***}	0.041^{***}	0.041^{***}	0.041^{***}	0.041^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mother has secondary sch education	0.011^{***}	0.011^{***}	0.011^{***}	0.011^{***}	0.011^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	143645	143645	143645	143645	143626
Within Country Location FE	Y	Y	Y	Y	Y
Interview Year FE	Y	Y	Y	Y	Y
Interview Month FE	Y	Y	Y	Y	Y
Child Age FE	Y	Y	Y	Y	Y
Enrollment t-1 X Age Group Controls	Y	Y	Y	Y	Y
Attainment t X Age Group Controls	Y	Y	Y	Y	Y
Enrollment t-1 X Country Controls	Y	Y	Y	Y	Y
Attainment t X Country Controls	Y	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). At last, we consider the rate of children reporting having school closed due to natural disaster in sub-national location as "MICS natural disaster measure". All measures before this one come from EM-DAT data.

Table C.4: Disaster and enrollment, heterogeneity across ages groups and countries

	(1)	(2)
Had disaster in most recent 12 months		
× Pakistan		
× Age 5–8	−0.105	−0.105
	(0.070)	(0.071)
× Age 9–12	−0.110	−0.101
	(0.070)	(0.071)
× Age 13–17	−0.101	−0.103
	(0.070)	(0.071)
× Bangladesh		
× Age 5–8	0.044***	0.029***
	(0.008)	(0.008)
× Age 9–12	−0.011	−0.009
	(0.007)	(0.007)
× Age 13–17	−0.027***	−0.019***
	(0.008)	(0.007)
× Other countries		
× Age 5–8	−0.005	−0.002
	(0.006)	(0.006)
× Age 9–12	−0.013**	−0.014***
	(0.005)	(0.005)
× Age 13–17	−0.013	−0.007
	(0.009)	(0.009)
# of months with disaster in the first 1000 days		
× Pakistan		
× Age 5–8	−0.006***	−0.005***
	(0.001)	(0.001)
× Age 9–12	−0.001**	−0.001
	(0.001)	(0.001)
× Age 13–17	−0.001	−0.000
	(0.001)	(0.001)
× Bangladesh		
× Age 5–8	0.003***	0.002*
	(0.001)	(0.001)
× Age 9–12	−0.002***	−0.001
	(0.001)	(0.001)
× Age 13–17	−0.003***	−0.003***
	(0.001)	(0.001)
× Other countries		
× Age 5–8	0.002***	0.001***
	(0.000)	(0.000)
× Age 9–12	−0.000	−0.001***
	(0.000)	(0.000)
× Age 13–17	−0.001	−0.002
	(0.001)	(0.001)
Observations	143645	143632
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 controls	*Y*	*Y*
Attainment t × age group controls	*Y*	*Y*
Enrollment t-1 × country controls	*Y*	*Y*
Attainment t × country controls	*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.

Table C.5: Regression of math score on disaster shock

	(1)	(2)	(3)
DB_A in Most Recent 12 Mo	0.319		0.350
	(0.696)		(0.704)
DB_A in Yr Prior 12 Mo Ago	−0.212		
	(0.447)		
DB_A After 1000 Days Until 2 Yr Before Survey Mo	−0.083		
	(0.115)		
DB_A in First 1000 Days of Life	-0.216^{***}		
	(0.070)		
DM_A in Most Recent 12 Mo		0.389	
		(0.350)	
DM_A in Yr Prior 12 Mo Ago		−0.159	−0.107
		(0.250)	(0.240)
DM_A After 1000 Days Until 2 Yr Before Survey Mo		-0.018^{*}	-0.018^{*}
		(0.010)	(0.010)
DM_A in First 1000 Days of Life		-0.024^{**}	-0.024^{**}
		(0.010)	(0.010)
Female	-0.398^{***}	-0.400^{***}	-0.400^{***}
	(0.037)	(0.037)	(0.037)
Mother is alive	0.202	0.201	0.201
	(0.162)	(0.162)	(0.162)
Father is alive	0.153	0.154	0.155
	(0.106)	(0.106)	(0.106)
Mother is living in same HH	0.145^{*}	0.147^{*}	0.146^{*}
	(0.079)	(0.079)	(0.079)
Father is living in same HH	-0.205^{***}	-0.206^{***}	-0.205^{***}
	(0.060)	(0.060)	(0.060)
Mother ever educated	0.981^{***}	0.980^{***}	0.980^{***}
	(0.058)	(0.058)	(0.058)
Mother has secondary sch education	0.814^{***}	0.813^{***}	0.813^{***}
	(0.048)	(0.048)	(0.048)
Observations	78141	78141	78141
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 X Cluster FE	*Y*	*Y*	*Y*
Country X A_{t-1} FE	*Y*	*Y*	*Y*

Note: This table shows regression result of Equation 3 using different measures for disaster shock. DB_A is an indicator being 1 if there was any type of disaster in the time span for each child, while DM_A means the number of months that child has experienced any type of disasters. In each column, four shocks covering one child's life cycle is included representing four time spans: first 1000 days of life, time between 1000 days of life and 2 years prior survey month, 1 year prior 12 months ago compared to survey month, and the most recent year (12 months).

Table C.6: Disaster and math test score, heterogeneity across country groups

	(1)	(2)
# of months with disaster in mid-child life		
× Pakistan	0.008	−0.001
	(0.017)	(0.017)
× Bangladesh	-0.051^{***}	-0.056^{***}
	(0.014)	(0.015)
× Other countries	0.032^{*}	0.048^{***}
	(0.018)	(0.019)
# of months with disaster in the first 1000 days		
× Pakistan	-0.089^{***}	-0.069^{***}
	(0.016)	(0.016)
× Bangladesh	0.025	0.020
	(0.019)	(0.020)
× Other countries	0.033^{*}	0.034^{*}
	(0.019)	(0.020)
Observations	78305	78141
Within country location FE	*Y*	
Country X cluster FE		*Y*
Interview year FE	*Y*	*Y*
Interview month FE	*Y*	*Y*
Child age FE	*Y*	*Y*
Country X Attainment t 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.

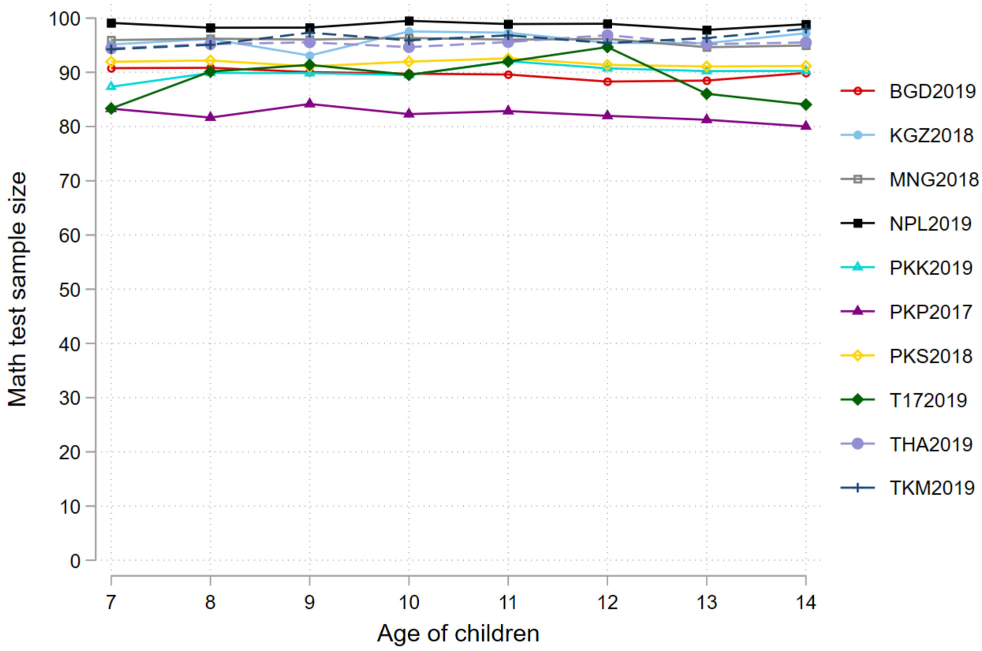
Table C.7: Disaster and math test score, heterogeneity across ages groups and countries

	(1)	(2)
# of months with disaster after 1000 days of life until 2 yr before survey month		
× Pakistan		
× Age 5–8	0.075	0.071
	(0.063)	(0.064)
× Age 9–12	−0.043	−0.036
	(0.035)	(0.036)
× Age 13–17	0.006	−0.009
	(0.029)	(0.029)
× Bangladesh		
× Age 5–8	−0.191***	−0.176***
	(0.045)	(0.048)
× Age 9–12	−0.013	−0.017
	(0.025)	(0.026)
× Age 13–17	−0.045**	−0.057**
	(0.021)	(0.023)
× Other countries		
× Age 5–8	0.023	0.031
	(0.025)	(0.025)
× Age 9–12	0.014	0.023
	(0.023)	(0.024)
× Age 13–17	0.012	0.022
	(0.023)	(0.024)
# of months with disaster in the first 1000 days		
× Pakistan		
× Age 5–8	−0.134***	−0.105**
	(0.042)	(0.043)
× Age 9–12	−0.052**	−0.021
	(0.022)	(0.023)
× Age 13–17	−0.030	−0.013
	(0.051)	(0.052)
× Bangladesh		
× Age 5–8	0.106**	0.107**
	(0.046)	(0.048)
× Age 9–12	0.058**	0.036
	(0.027)	(0.029)
× Age 13–17	−0.006	0.001
	(0.024)	(0.026)
× Other countries		
× Age 5–8	0.006	0.011
	(0.028)	(0.028)
× Age 9–12	0.008	−0.001
	(0.025)	(0.025)
× Age 13–17	0.086***	0.062**
	(0.026)	(0.031)
Observations	78305	78141
Within country location FE	*Y*	
Country X cluster FE		*Y*
Interview year FE	*Y*	*Y*
Interview month FE	*Y*	*Y*
Child age FE	*Y*	*Y*
Country X Attainment t FE	*Y*	*Y*

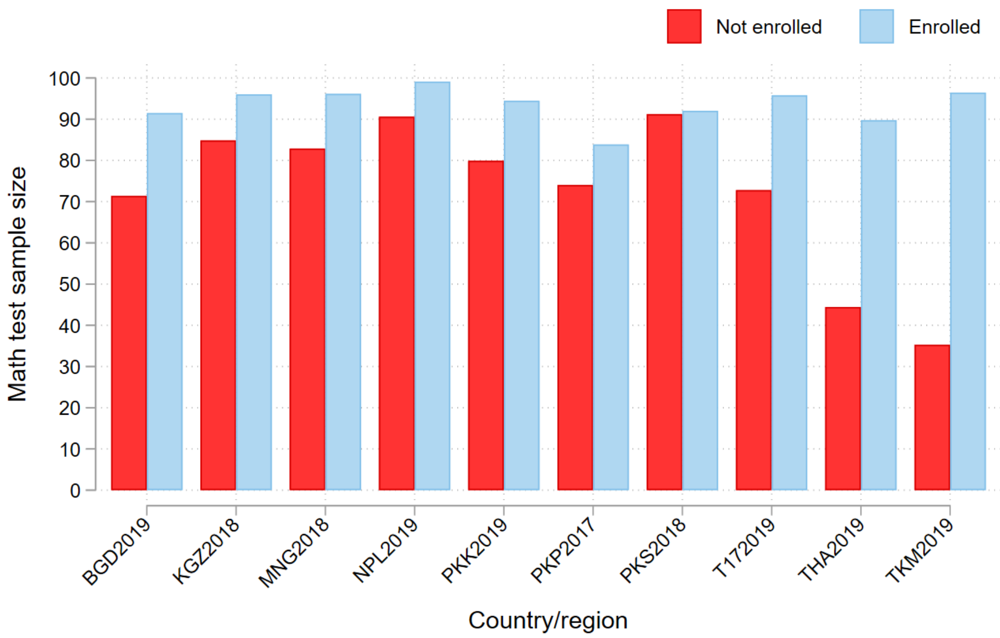
Note: This table shows heterogeneous analysis across countries and ages of disaster effect on math test score. This is corresponded with Equation 3 with interaction between disaster shocks, age groups, and country groups.

Figure C.1: Math Test Sample Size

(a) Math Test Sample Size by Ages and Countries



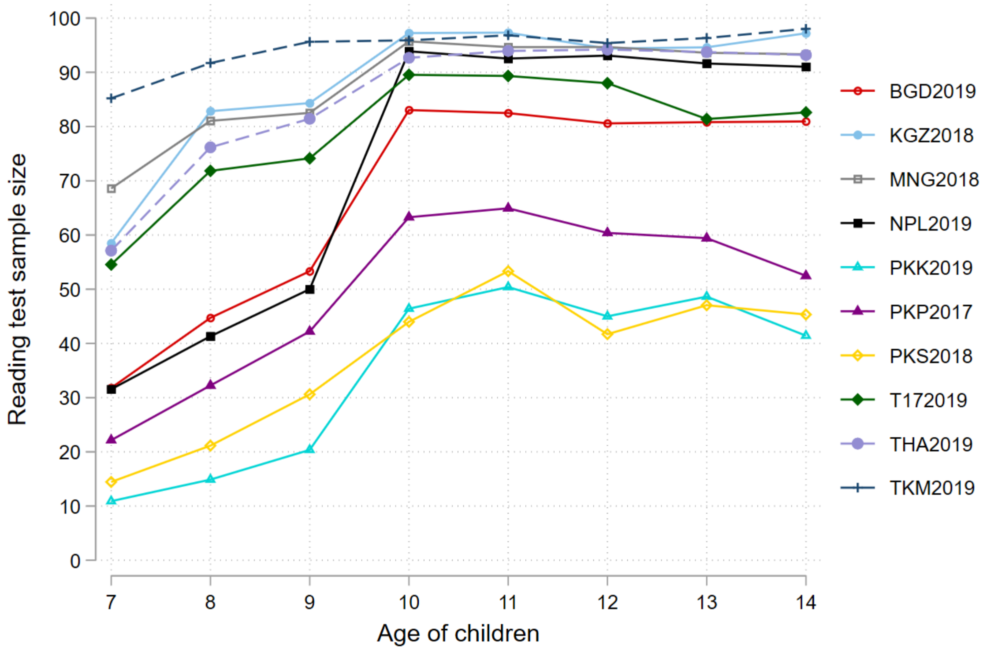
(b) Math Test Sample Size by Enrollment Status in Current Year Across Countries



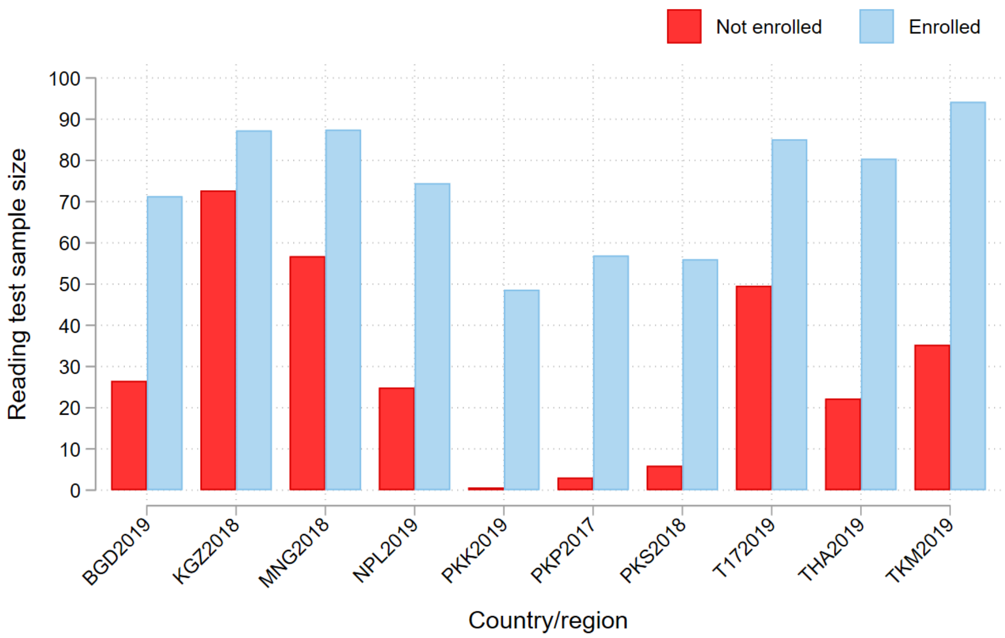
Note: Fractions show share of sample by age and country reporting math test score, consistent share across ages, some variation across countries. We notice whether the child has Math test Score is related to if she is enrolled in school in the current period. We find much larger share with math test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

Figure C.2: Reading Test Sample Size

(a) Reading Test Sample Size by Age

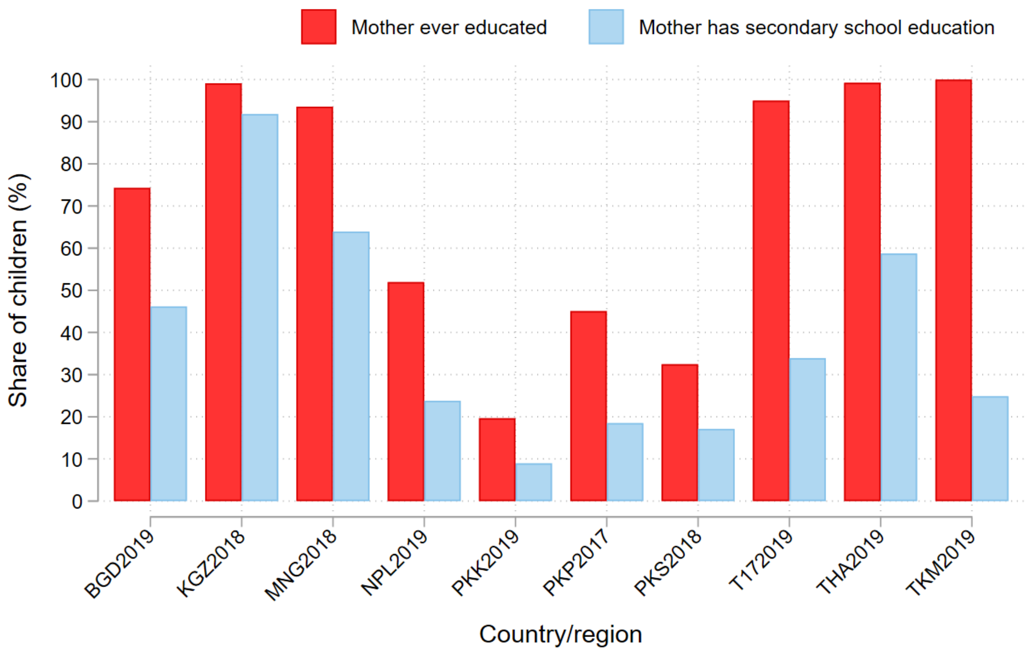


(b) Reading Test Sample Size by Enrollment Status Across Countries



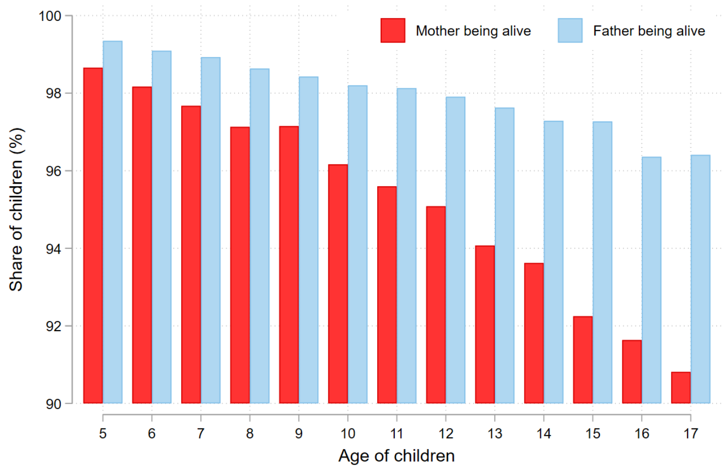
Note: Fractions show share of sample by age and country reporting reading test score, consistent share across ages, some variation across countries. We notice whether the child has reading test Score is related to if she is enrolled in school in the current period. We find much larger share with reading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

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

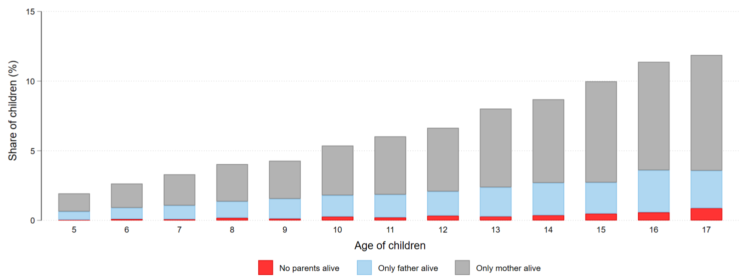


Note: This table show (1) share of children whose mother has had any kind of education (2) share of children whose mother has secondary school education by countries. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber Pakhtunkhwa, **PKP**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

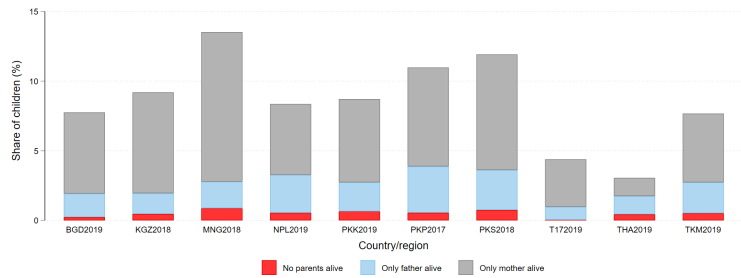
Figure C.4: Share of Children with Mother or Father Alive by Ages



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



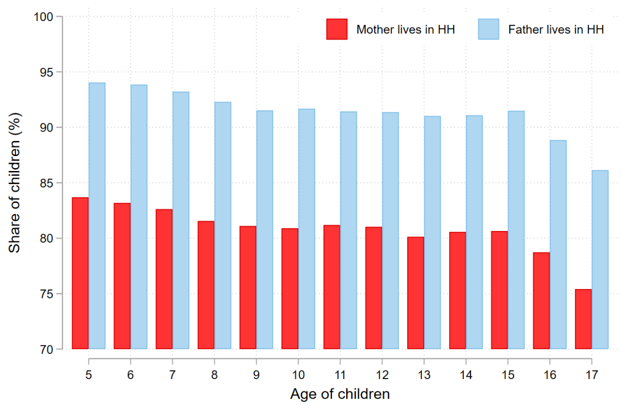
(b) Share of Children with Both or One Parent Alive by Ages



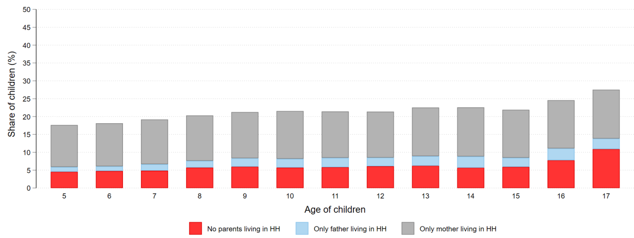
(c) Share of Children (Age $\geq$ 12) with Both or One Parent Alive by Countries

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

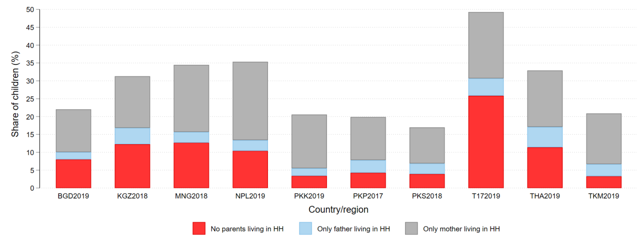
Figure C.5: Share of Children Living with Parents



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



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

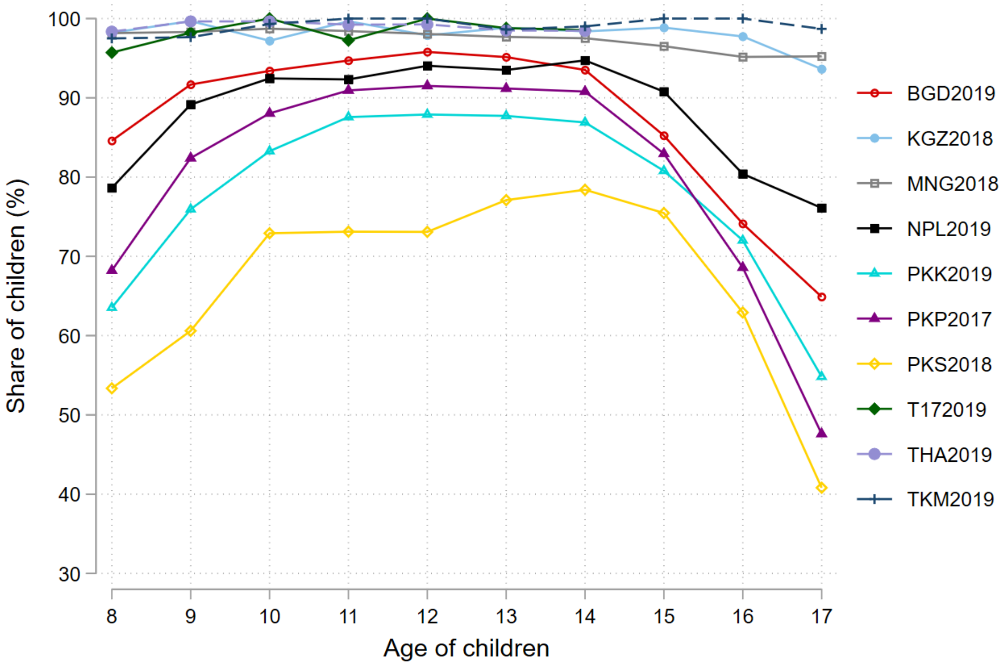


(c) Share of Children (Age $\geq$ 12) Living with Both of One Parent by Countries

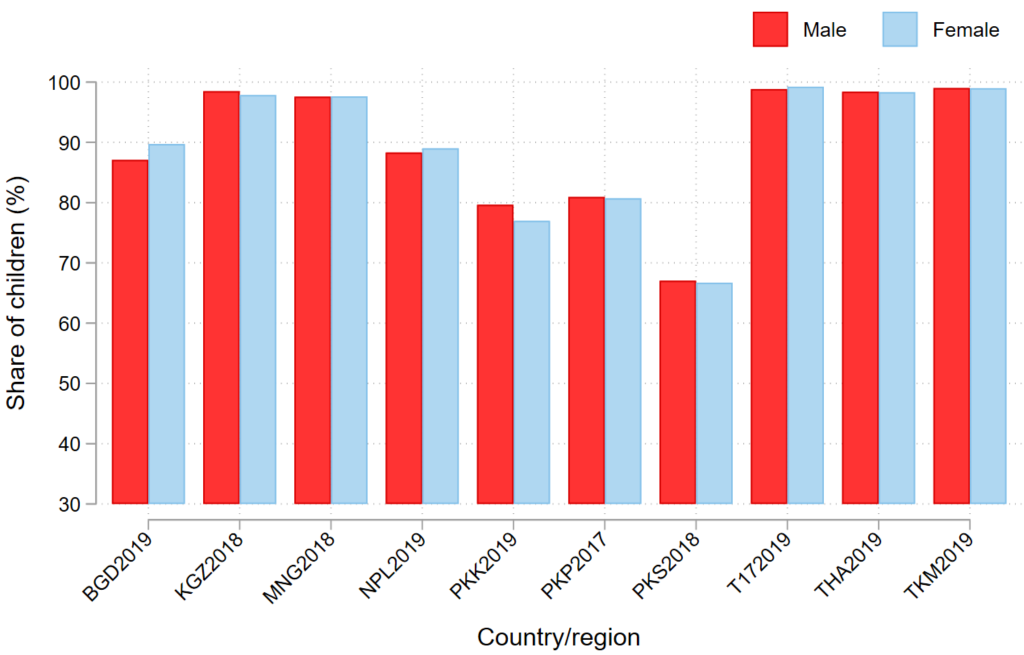
Note: Panel (a) shows the share of children living with either mother or father by ages. Panel (b) and (c) show the share of children living with both parents or one of them by ages. The four categories include living with both parents (not included in the bar), with just mother, with just father, not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

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

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



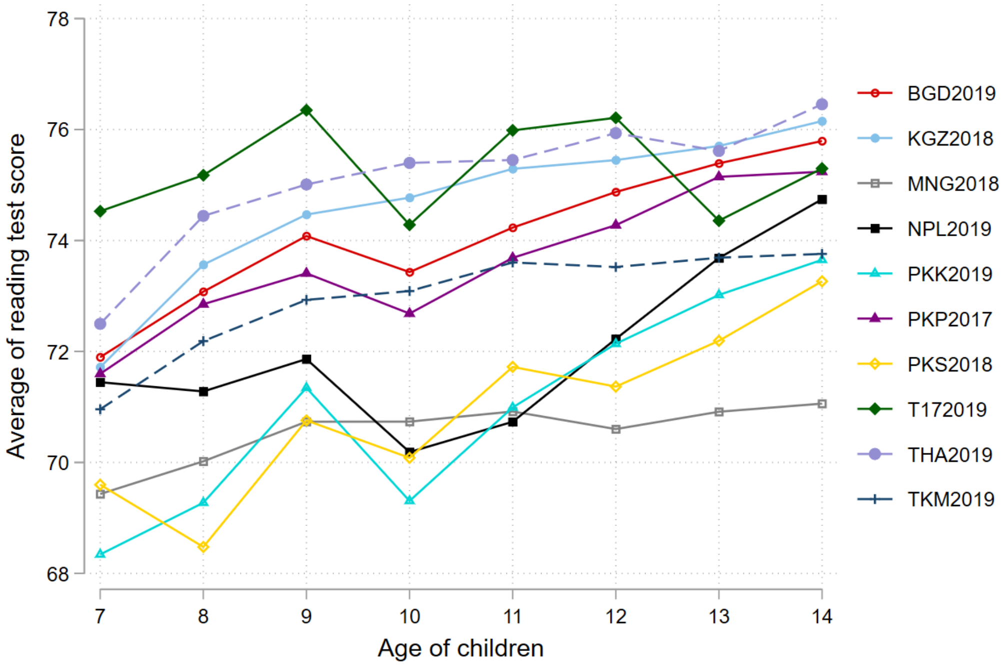
(b) Progression Rate in Last Year by Gender and Countries ($\geq$ age 8)



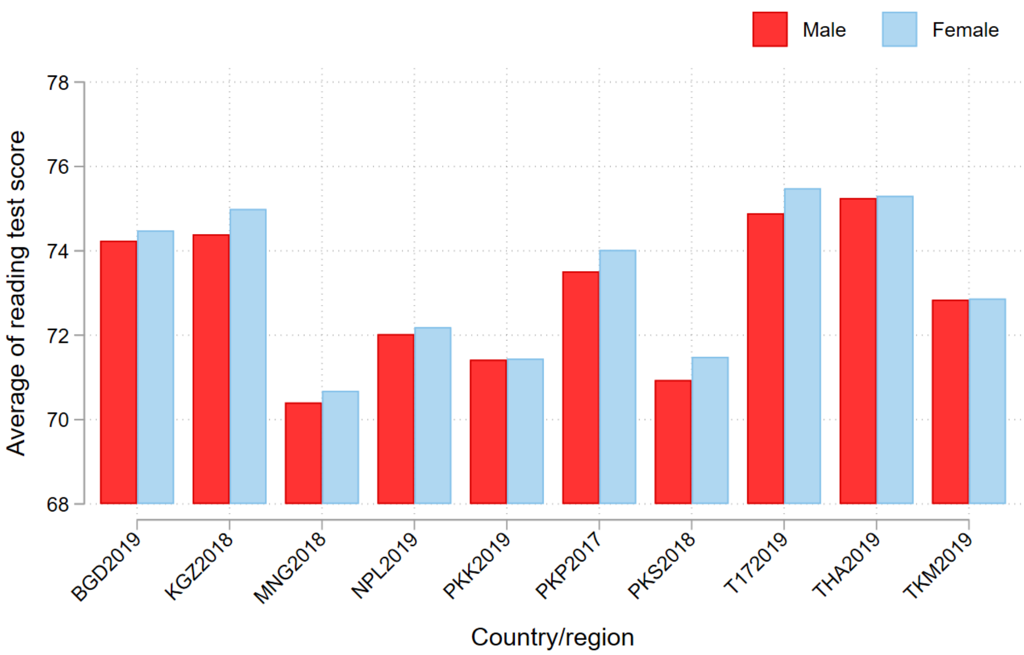
Note: The table shows progression rates. Progression is equal to 1 if a child attends a grade and successfully completes the grade, leading to an increase in grades completion by 1 years. Countries included are: Bangladesh (2019, **BGD**), Nepal (2019, **NPL**), Pakistan (2017-2019, **PKK** for Khyber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

Figure C.7: Distribution on Reading Test Score

(a) Reading Test Score Across Ages and Countries



(b) Reading Test Score by Gender and Countries (Age 7-14)



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