Are Disasters Disastrous for Learning? Evidence from Seven Asian Countries

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SWUFE School of Economics Workshop

December 27, 2023

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Introduction

Motivation

- Between 1970 and 2019, climate change and extreme weather events have caused a surge in natural disasters (UN 2021).

- Globally, Asia accounted for...
  - 1/3 weather, climate, and water related disasters.
  - 1/2 of deaths.
  - 1/3 of associated economic losses.

"[The Asia-Pacific region] remains the most disaster-prone region...In 2022, over 140 disasters struck...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, v, 6)*

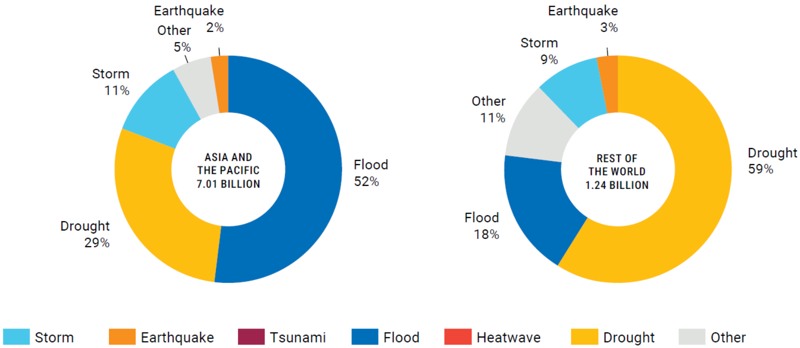

Figure 1: People affected by disasters in the Asia-Pacific region and the rest of the world, 1970-2022

Motivation

- ***Children* are potentially heavily exposed.**
  - About one billion children across the world are at an 'extremely high risk' of experiencing impacts of climate crisis (UNICEF 2021).
  - Climate change tends to interact with 'non-climatic stressors and entrenched structural inequalities to shape vulnerability (Olsson et al. 2014).
- **Exposure is distributed *unequally* among children.**
  - Exposure to environmental stressors is highly prevalent and unequally distributed along socioeconomic lines (Torche 2018).
  - Negative effects are correlated with social disadvantages (Fuller 2014; Cutter et al. 2003; Zahran et al. 2008).
- ***Short-term* impacts on enrollment could lead to *long-term* effects of disasters on human capital development and accumulation for children.**

This paper

- What are impacts of exposure to natural disasters on children's educational outcomes?
- Are there heterogeneous impacts on school enrollment and cognitive achievements for children along gender, age, and SES gradients?
  - We link **survey data on children** with **global time- and geo-coded disaster records.**
  - We provide one of the first **cross-nation and cross-disaster** analysis of effects of disruptive natural disasters on human capital accumulation.

This paper

- **More than 140,000 children in seven Asian countries of age 5-17**
  - Low- and middle-income countries
  - Pre-pandemic data available
  - South Asia (Bangladesh, Nepal, Pakistan), East Asia and the Pacific (Mongolia, Thailand), and Central Asia (Kyrgyzstan, Turkmenistan)
- **About 500 natural disasters from 1998 to 2019**
  - All have led to substantial loss of human life
  - Various categories: flood, storm, drought, earthquake...

This paper

- Do relative timing when exposed to natural-disaster shocks matter impacts' sizes?
  - We provide first estimates distinguishing between separate effects of **current and earlier in life** disaster shocks.
  - We focus on **first 1000 days of life** (conception-2 years old).
    - Natural disasters cause changes in prenatal stress (Andrabi et al. 2021; Charil et al. 2010; Fuller 2014).
    - Central nervous system and brain grow rapidly between 8 and 25 weeks post-conception which is essential for cognitive development (Almond et al. 2009).
- Empirical strategy
  - Enrollment decision equation.
  - Human capital production functions.

Potential mechanisms

- Direct: disasters $\longrightarrow$ educational outcomes.
  - **Disasters can interrupt learning process.**
    - Worldwide 875 million school children live in high-seismic-risk zones, with 32 million of these children newly enrolled in primary schools (Wisner et al. 2004).
    - In Pakistan in 2010, 11,906 schools with > one million children were affected by natural disasters - used as shelter (2,674) or damaged (9,232) (Change et al. 2013).
  - **Schools serve as a refuge place when they are more resilient than houses.**
    - Parents may be unable to provide as much care for children at home.

Potential mechanisms

- Indirect: disasters $\longrightarrow$ other stressors $\longrightarrow$ educational outcomes.
  - **Health shock on children**
    - Exposure to disasters affect birth outcomes (Currie 2013, Glynn et al. 2001, Torche 2011, Oyarzo et al. 2012, Tan et al. 2009).
    - Disasters reduce children's physical capacity to attend school.
  - **Income and health shock on family**
    - Natural disasters affect employment, wages, and assest prices (Barro 2009, Belasen and Polachek 2008).
    - Household resource availability for schooling may be lower.
    - Opportunity costs of schooling may increase as children compensate for lost parental income by taking up greater household and wage work responsibilities (Alam 2015; Bandara et al. 2015; Guarcello et al. 2010).

Preview of results

- Average effects from disaster exposures on enrollments and math skills
  - There are significant negative effects of early life disaster exposures.
  - There are weaker or no corresponding effects from recent disaster exposures.
- Age patterning of enrollment and learning effects of disaster exposure
  - There is a weak but increasingly negative relationship between recent disaster exposure and enrollment as children age.
  - There are more persistent negative relationships between early life disaster experience and enrollments through school-going ages.
  - This differs across national settings.
- Heterogeneity across gender
  - Early life shock affects school enrolment of children in both genders negatively.
  - Although impact on school enrolment is greater for boys than girls, cognitive performance of girls is harder hit than boys in older cohort.

Related literature and contribution

- **We consider early life exposures as well as recent disaster shocks.**
  - Children exposed to hurricanes *in utero* have lower scores in third grade (Fuller 2014).
  - Prenatal exposures have negative effects on educational or economic performance later in life (Almond and Mazumder 2005, Almond et al. 2009).
- **We explore heterogeneity globally and locally with large sample.**
  - Negative effects are correlated with social disadvantages (Fuller 2014, Cutter et al. 2003, Zahran et al. 2008).

Related literature and contribution

- **Most existing studies of natural disasters' effects on children focus on a *specific large-scale disaster.***
  - 2017 Pohang earthquake in South Korea (Cho and Kim 2023)
  - 1976 Tangshan earthquake in China (Tian et al. 2022)
  - 1985 earthquake in Chile (Ciraudo 2020)
  - 1987-89 locust plague in Mali (De Vreyer et al. 2015)
  - 2009 Bushfire in Australia (Gibbs et al. 2019)
- **There are limited studies on broad groups of disasters yet *not study educational outcomes in developing countries.***
  - U.S. (Opper et al. 2023, Simeonova 2009, Currie and Rossin-Slater 2013)

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Data

Data on educational outcomes and school systems

UNICEF Multiple Indicator Cluster Surveys (MICS)

- General information
  - International multi-purpose household survey. 28 years, 118 countries, 355 surveys.
  - Integral part of plans and policies of many governments.
  - Major data source for > 30 Sustainable Development Goals indicators.
- 6th round (MICS6)
  - Child age 5-17: school enrollment, attainment, survey-administered literacy and numeracy assessment tests.
  - Parental and household background.

Data on natural disasters

EM-DAT International Natural Disaster Database (1900-2023)

- Time- and geo-coded (Center for Research on the Epidemiology of Disaster).
- Sources: UN agencies, non-governmental organizations, insurance companies, research institutes, and press agencies.
- Entry criteria: (a) 10 or more people killed, (b) 100 or more people affected, (c) declaration of a state of emergency, (d) call for international assistance.
- **Context variables**: disaster type, administrative level, affected location.
- **Impact variables**: number of deaths, injured, missing, total affected, economic damages, insured losses, sectors affected, infrastructure affected.

Linking EM-DAT and MICS data

OCHA Humanitarian Data

- EM-DAT variables **Locations** and **GeoLocation** record location names affected by each disaster.
- Using data on sub-national administrative boundaries (Humanitarian Data), we match disasters in EM-DAT to locations in MICS.
- Using starting and ending year and month of disasters in EM-DAT, interview and birth year and month of children in MICS, we construct children life-cycle disaster exposure histories.

Disaster shock

Binary and continuous measures of disaster intensity in particular time spans

$$DM^p_{il,j} = \sum_{\text{mo=start mo. of j}}^{\text{end mo. of j}} DI^p_{il,mo} \quad (1)$$

$$DB^p_{il,j} = 1\{DM^p_{il,j} \geq 1\}$$

- $DI^p_{il,mo}$: Binary indicator of disaster for each child in each month, 1 if location l in month mo has experienced type p disaster intensity.
- $DM^p_{il,j}$: # of months in disaster for child i in location l during period j.
- $DB^p_{il,j}$: binary indicator for existence in time span j of type p disaster intensity.

Disaster shock

Types of disaster intensity denoted by p

- Type A: any type of disaster
- Type B: only flood
- Type C: 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.

Summary statistics

MICS6 overview and key statistics for children 5-17

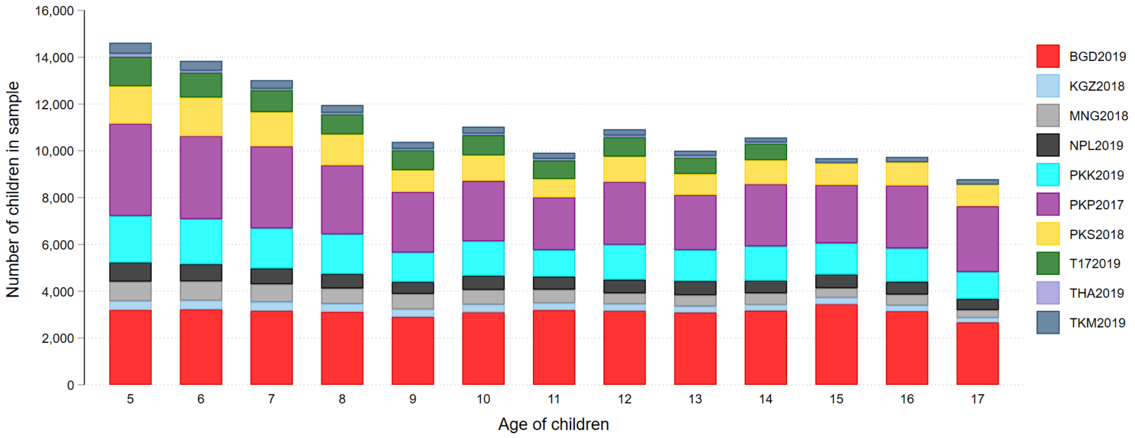
Country	Year	Start	End	Obs	Geo info ‡		Age	Female	Enrollment rate	Mother ever educated
					Geo-id	N	Mean	Share		
South Asia										
Bangladesh	2019	01/19	06/01	40617	District	64	10.95	0.48	0.89	0.74
Nepal	2019	05/04	11/13	7824	Region	7	10.55	0.50	0.93	0.52
Pakistan	2017-19	2017 12/03	2019 10/23	71121	District	97	10.49	0.48	0.86	0.36
East Asia and the Pacific										
Mongolia	2018	09/17	12/24	7628	Region	9	10.06	0.49	0.96	0.94
Thailand	2019	05/18	12/03	9608	Changwat	18	9.03	0.48	0.99	0.95
Europe and Central Asia										
Kyrgyzstan	2018	09/06	11/19	3897	Oblast	9	10.34	0.47	0.96	0.99
Turkmenistan	2019	05/02	08/02	3776	Region	6	10.08	0.48	1.00	1.00

Note: At the smallest geo-identifier available, we compute the share of enrolled in school reporting school closure due to natural disasters (or teacher absenteeism) in the past year and s.d. across geo-identifiers. Smallest geo-identifiers differs across countries.

Child and parental characteristics

	Mean	SD	Min	Max	N
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

Sample sizes across countries and ages

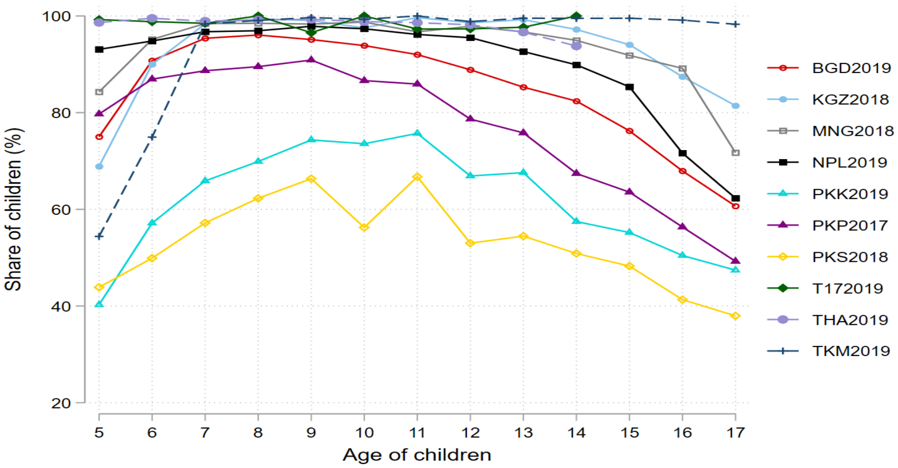


Enrollment, attainment, and math score

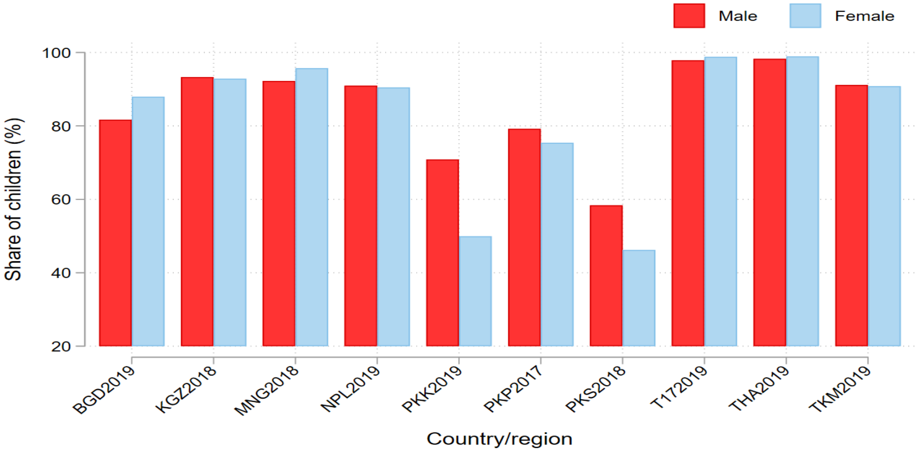
	Mean	SD	Min	Max	N
Ever enrolled	0.88	0.33	0.00	1.00	144426
Enrollment in last school year	0.74	0.44	0.00	1.00	144394
Enrollment in this school year	0.79	0.41	0.00	1.00	144410
Attainment (highest)	3.29	3.34	0.00	16.00	144358
Attainment at start of last school year	2.69	3.06	0.00	16.00	144360
Attainment at start of this school year	3.25	3.32	0.00	16.00	144358
Math score	14.19	7.42	0.00	54.00	78,704

- Math test is for children 7-14 only.

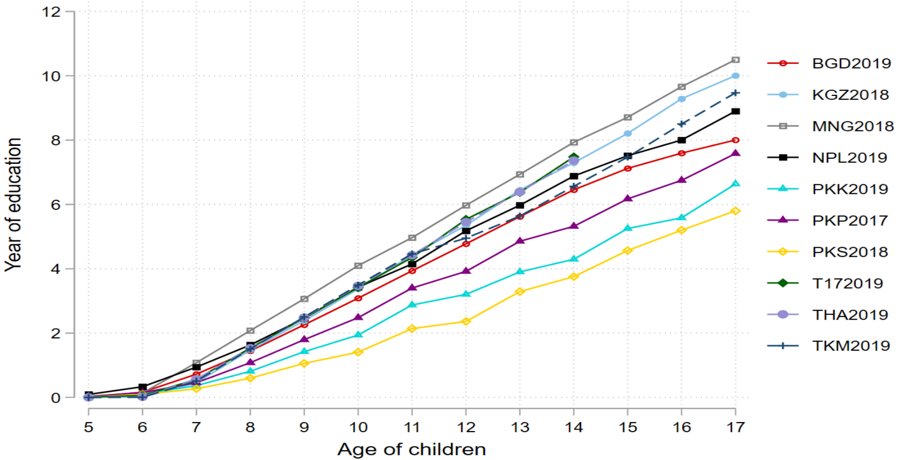
Enrollment rates in survey year by ages and countries



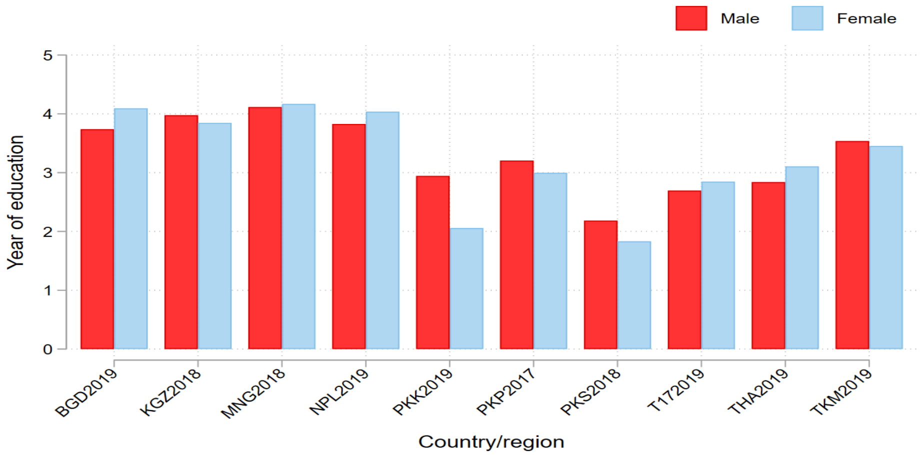
Enrollment rates in survey year by gender and countries



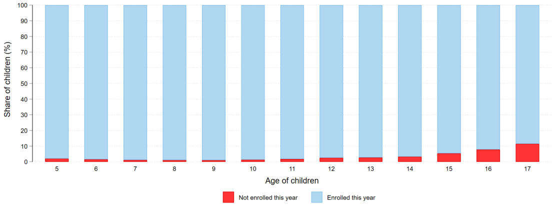
Average highest grade completed by ages and countries

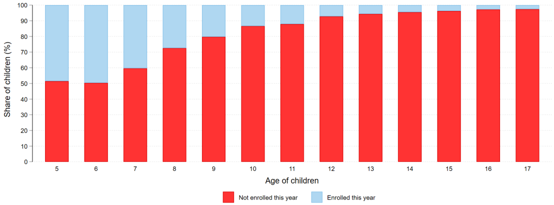


Average highest grade completed by gender and countries



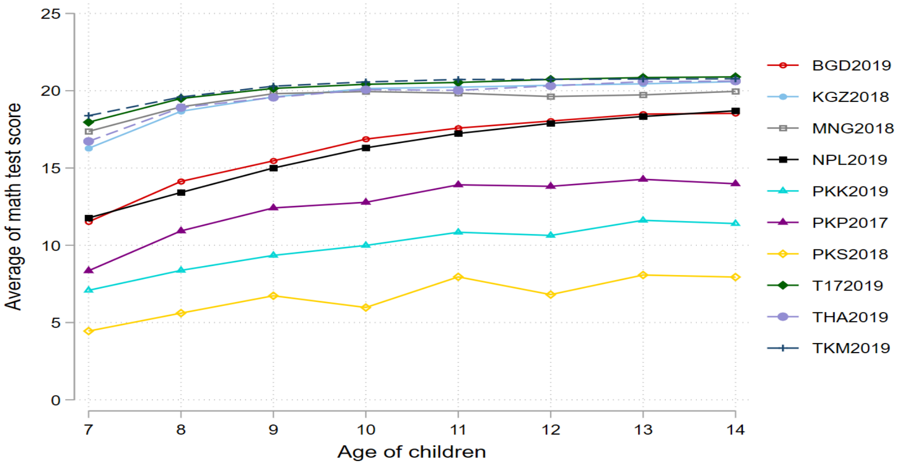
Enrollment transition probabilities by ages



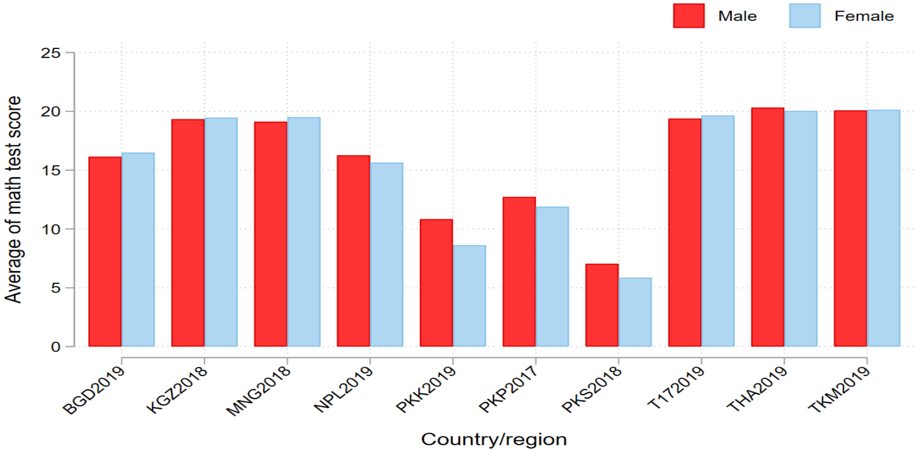


- Share of children who were enrolled in the year prior to the survey and continued to enroll in the survey year is greater than 95% up to age 14, but falls to 88% by age 17.
- Share of children who come back to enrollment after not enrolled in the last year before the survey decreases with age and falls below 10% after age 11.

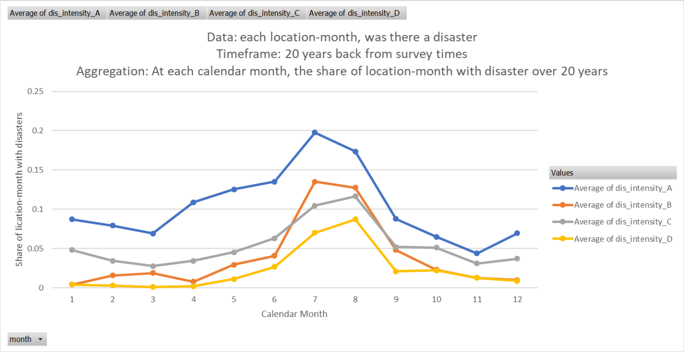
Average of math test score by ages and countries



Average of math test score by gender and countries



Average shares of location-month disasters in calendar months over 20 years



- Types: A) all disasters, B) only floods, C) only severe disasters (> 50 people dead or injured, or > 5,000 people affected), D) only severe floods.
- For all types, during summer locations are hit by disasters most.
- Focusing on only one category omits large proportion of overal shocks.

Location- and life-cycle-specific disaster shocks of children

	Mean	SD	Min	Max	N
Had recent disaster					
in survey mo	0.08	0.27	0.00	1.00	144471
in this year prior survey mo	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 given child life-cycle-specific disaster history					
in child's first 1000 days of life	0.58	0.49	0.00	1.00	144471
between 1000 days and 2 yr before survey mo	0.70	0.46	0.00	1.00	144471

Key variables by age groups and periods

Mean	Early life	Mid-child life	Recent year
Length of period (mo.)	By def. 33	84	By def. 12
# of mo. in disaster, share of children having experienced disasters			
Overall	3	7.8	57%
Age 5-8	2		55%
Age 9-12	3		56%
Age 13-17	4		59%
Age 7-9	2	5.4	56%
Age 10-12	3	8	56%
Age 13-14	4	10.5	56%
Math test score	**Overall**	**Boys**	**Girls**
Age 7-9	12.3	12.4	12.1
Age 10-12	15.2	15.4	15
Age 13-14	15.9	16	15.6

Methodology

Enrollments and disaster shocks

Estimation strategy

$$E_{ilt} = \alpha_0 + \psi_0 \cdot E_{il,t-1} + \psi_1 \cdot A_{ilt} + \sum_{j \in \text{TimeSpan}} \alpha^p \cdot D^p_{ilj} + \theta X'_i + \mu_l + \mu_{g_i(t)} + \mu_t + \epsilon_{ilt} \quad (2)$$

- $E_{il,t}$ - enrollment status of child i in location l in school year t.
- $\text{TimeSpan} = \{m12to1, first1000days\}$ - most recent year up to survey month, first 1000 days of life.
- A_{ilt} - year of education completed at start of school year t.
- D^p_{ilj} - natural disaster shock of type p (eg. type A means any type of disaster).
- X - individual and parental characteristics - parental age, mother's education, whether parents are alive, and whether child resides with parents.
- μ_l, $\mu_{g_i(t)}$, μ_t - fixed effects of sub-national location, child age, and survey time.

Math test scores and disaster shocks

Estimation strategy

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

- S_{ilm} - score on the MICS-administered math test achieved by child i in location l in survey month m.
- TimeSpan $= \{m12to1, age25mtolastyear, first1000days\}$ - most recent year up to survey month, first 1000 days of life, and mid-child life in between.
- D^p_{ilj} - natural disaster shock of type p (eg. type A means any type of disaster).
- $\mu_{c,Ai(m)}$ - country- and attainment-specific fixed effects.

Results

Effects of disasters on enrollments

	(1)	(2)	(3)
Had disaster in last 12 months	-0.003	-0.002	-0.004
# of mos. with disaster in first 1000 days of life	-0.002***	-0.002***	-0.001***
Enrollment in year $t-1$	0.648***	0.641***	0.388***
Attainment at start of t	0.025***	0.024***	0.012***
Female		-0.015***	-0.006***
Mother is alive		-0.015***	-0.009*
Mother is alive × living in same HH		0.029***	0.025***
Father is alive		0.013***	0.012***
Father is alive × in same HH		-0.005**	-0.005**
Mother ever educated		0.037***	0.041***
Mother ever educated × has secondary education		0.004**	0.011***
Observations	144354	143645	143645

Disasters and enrollments: heterogeneity across age groups

	(1)	(2)
Had disaster in last 12 months		
× Age 5–8	0.008*	0.002
× Age 9–12	-0.009**	-0.005
× Age 13–17	-0.012**	-0.010*
# of months with disaster in first 1000 days of life		
× Age 5–8	0.001***	0.001*
× Age 9–12	-0.002***	-0.001***
× Age 13–17	-0.001***	-0.001***
Observations	143645	143622
Within-country location FE	Y	
Country × cluster FE		Y

Disasters and enrollments: heterogeneity across gender and age groups

	(1)	(2)
Had disaster in most recent 12 months		
× Male × Age 5–8	0.013**	0.072**
× Age 9–12	-0.010**	0.049
× Age 13–17	-0.017***	0.041
× Female × Age 5–8	0.003	0.064**
× Age 9–12	-0.009*	0.051*
× Age 13–17	-0.008	0.051*
# of months with disasters in first 1000 days of life		
× Male × Age 5–8	0.001**	0.001***
× Age 9–12	-0.003***	-0.003***
× Age 13–17	-0.001***	-0.001***
× Female × Age 5–8	0.001**	0.001**
× Age 9–12	-0.000	-0.000
× Age 13–17	-0.001*	-0.001**
Observations	143645	143622
Within-country location FE	Y	
Country × cluster FE		Y

Effects of disasters on math 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 first 1000 days of life	-0.037***	-0.030***	-0.028***	-0.024**
	(0.010)	(0.010)	(0.010)	(0.010)
Observations	78657	78502	78305	78141
Within-country location FE	Y		Y	
Country X cluster FE		Y		Y

Disasters and math scores: heterogeneity across age groups

	(1)	(2)
# of months with disaster in mid-child life		
× Age 7–9	-0.006	0.003
× Age 10–12	-0.005	0.002
× Age 13–14	-0.009	-0.002
# of months with disaster in first 1000 days of life		
× Age 7–9	-0.035**	-0.022
× Age 10–12	0.016	0.012
× Age 13–14	-0.020	-0.016
Observations	78303	78139
Within country location FE	Y	
Country X cluster FE		Y

Disasters and math scores: 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

Disasters and math scores: heterogeneity across gender and age groups

	(1)	(2)
# of months with disaster in mid-child life		
× Male × Age 7 to 9	-0.022	-0.014
× Age 10 to 12	-0.013	-0.006
× Age 13 to 14	-0.019	-0.010
× Female × Age 7 to 9	0.009	0.018
× Age 10 to 12	0.003	0.009
× Age 13 to 14	-0.000	0.005
# of months with disaster in first 1000 days of life		
× Male × Age 7 to 9	-0.032*	-0.023
× Age 10 to 12	0.013	0.018
× Age 13 to 14	0.005	-0.005
× Female × Age 7 to 9	-0.039**	-0.021
× Age 10 to 12	0.018	0.005
× Age 13 to 14	-0.044**	-0.025
Observations	78305	78141
Within country location FE	Y	
Country X cluster FE		Y

Conclusions and discussion

Summary of findings

1. Overall significant negative effects of early life exposure on enrollment and math skills.
2. Weaker/no effects of recent exposure.
3. Weak but increasingly negative relationship between recent exposure and enrollment as children age.
4. More-persistent negative relationship between early exposure and enrollment through school-going ages.
5. Age patterns of effects of exposure differ across countries.
6. Negative effects from early life exposure on school enrolment of both genders.
7. Although impacts on enrolment are greater for boys than girls, cognitive performance of girls are harder hit than the boys in older cohort.

Limitations and challenges

- MICS data lacks information on the migration status of children, introducing bias when treating all children as residing in the same location since conception.
- The effectiveness of each government in recording and reporting disasters depends on the capabilities of individual locations.
- Entry criteria of EM-DAT can result in exclusion of more localized disasters.
- The locations affected by disasters in EM-DAT do not precisely align with the administrative levels in MICS. Consequently, alternative matching strategies should be explored.

Next steps

- We utilize the mothers' locations to establish the migration rate within our sample, and additionally adjust the early-life locations of the children.
- To ensure robustness, we will incorporate a range of intensity levels for disaster shocks in our models assessing enrollment status and math scores.

Appendix

Context Variables (EM-DAT Example)

- Example showing 3 natural disasters in Bangladesh (continued in next slide).

Disaster Type	Origin	OFDA Response	Dis Mag Value	Dis Mag Scale	Latitude	Longitude	Admin1 Code	Admin2 Code	Geo Locations
Flood	Torrential Rain		3882	Km2	23.226	92.13			
Storm				Kph			577		Dhaka (Adm1)
Flood		Yes		Km2				5761...	Bagerhat Barguna... (Adm2)
Storm			130	Kph					

Impact Variables (EM-DAT Example)

- Example showing 3 natural disasters in Bangladesh (continued from last slide).

Start Year	Start Month	Start Day	End Year	End Month	End Day	Total Deaths	No Injured	No Affected	Total Damages, Adjusted ('000 USD)	Total Damages ('000 USD)
2018	5	20	2018	5	22	21		14000		
2019	3	31	2019	3	31	15				
2019	6		2019	7	28	114		7600000	75000	85854
2019	11	9	2019	11	10	40	71	251506	5785	6622

Enrollments and disaster shocks

Enrollment decision model

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).

- Not enrolled in $t \Rightarrow$ no additional grade completion progress.
- Enrolled in $t \Rightarrow$ prob. of passing grade and increasing attainment.
- Utility from enrollment comes from expected value minus cost: $u(\text{enroll})_t = E(\text{increased attainment})_{t+1} - C(\text{enroll})_t$.
- Decision makers jointly consider key state var.: grade completed, prior enrollment decision, age of child.

Math test scores and disaster shocks

Human capital production function

Linear model is assumed to capture the facet of education: it is a cumulative process.
A_{ig} involves whole history of inputs providing basic knowledge (Todd and Wolpin 2003, Hanushek and Rivkin 2012).

$$A_{ig} = f(Sch_i, Fam_i, \pi_i) = \sum_{g=0}^{G} \psi Sch_{ig} + \sum_{g=0}^{G} \gamma Fam_{ig} + \sum_{g=0}^{G} \pi_{ig} + \epsilon_{ig}$$

- A_{ig} - achievement of student i in grade g.
- Sch, Fam - vector of school and peer, family and neighborhood inputs.
  π - individual ability.

$$S_{im} = f(D_{im}, X_{im}) \implies = \sum_{m=-9}^{M} \lambda D_{im} + \sum_{g=-9}^{M} \theta X_{im} + \epsilon_{im} \tag{4}$$

- S_{im} - score in month m.
- X - all factors other than disasters.
- D - individual- and time-specific disaster shocks. This would normally be part of ϵ.

Math test scores and disaster shocks

Human capital production function

$$S_{im} = f(D_{im}, X_{im}) = \alpha_1 D_{i1} + \alpha_2 \sum_{m \in \text{mid-child life}} D_{im} + \alpha_3 D_{i3} + \sum_{g=-9}^{M} \theta X_{im} + \epsilon_{im} \quad (5)$$

	D_{i1} Early life	D_{i2} 3-4	D_{i3} 5-6	D_{i4} 7-8	D_{i5} 9-10	D_{i6} 11-12	D_{i7} 13-14
$S_{i7}, 13-14$	λ_{71}	λ_{72}	λ_{73}	λ_{74}	λ_{75}	λ_{76}	λ_{77}
$S_{i6}, 11-12$	λ_{61}	λ_{62}	λ_{63}	λ_{64}	λ_{65}	λ_{66}	
$S_{i5}, 9-10$	λ_{51}	λ_{52}	λ_{53}	λ_{54}	λ_{55}		
$S_{i4}, 7-8$	λ_{41}	λ_{42}	λ_{43}	λ_{44}			

- α_1 - effects of shocks in early life.
- α_2 - homogeneous effects of shocks in mid-child life.
- α_3 - effects of shocks in recent shocks.
- S - outcome across age 7-14.
- D - disaster shocks in each periods.

Disasters and enrollments: heterogeneity across gender

	(1)	(2)
Had disaster in last 12 months		
× Male	-0.003	0.056*
	(0.005)	(0.030)
× Female	-0.005	0.056*
	(0.005)	(0.030)
# of months with disaster in first 1000 days of life		
× Male	-0.002***	-0.002***
	(0.000)	(0.000)
× Female	-0.000	-0.000
	(0.000)	(0.000)
Observations	143645	143622
Within-country location FE	Y	
Country × cluster FE		Y

Disasters and enrollments: heterogeneity across country groups

	(1)	(2)
Had disaster in last 12 months		
× Pakistan	-0.104	0.034
× Bangladesh	0.001	0.256**
× Other countries	-0.009*	0.035
# of months with disaster in first 1000 days of life		
× Pakistan	-0.001	-0.001*
× Bangladesh	-0.005***	-0.005***
× Other countries	0.001***	0.001***
Observations	143645	143622
Within-country location FE	Y	
Country × cluster FE		Y

Disasters and enrollments: heterogeneity across gender and age groups in Pakistan

	(1)	(2)
Had disaster in most recent 12 months		
× Male × Age 5–8	-0.043	-0.075
× Age 9–12	-0.072	-0.104
× Age 13–17	-0.102	-0.134
× Female × Age 5–8	-0.029	-0.057
× Age 9–12	-0.062	-0.092
× Age 13–17	-0.087	-0.119
# of months with disasters in the first 1000 days		
× Male × Age 5–8	-0.000	0.000
× Age 9–12	-0.002**	-0.002
× Age 13–17	0.001	0.000
× Female × Age 5–8	-0.007***	-0.008***
× Age 9–12	-0.001	-0.001
× Age 13–17	0.001	0.001
Observations	70728	70728
Within-country location FE	Y	
Country × cluster FE		Y

Disasters and enrollments: heterogeneity across gender and age groups in Bangladesh

	(1)	(2)
Had disaster in most recent 12 months		
× Male × Age 5–8	0.001	0.289**
× Age 9–12	-0.004	0.282**
× Age 13–17	0.005	0.290**
× Female × Age 5–8	-0.011	0.279**
× Age 9–12	-0.006	0.283**
× Age 13–17	0.002	0.290**
# of months with disasters in the first 1000 days		
× Male × Age 5–8	0.001	0.001
× Age 9–12	-0.001	-0.000
× Age 13–17	0.001	0.001
× Female × Age 5–8	0.002	0.002
× Age 9–12	0.002*	0.002*
× Age 13–17	-0.001	-0.001
Observations	40542	40542
Within-country location FE	Y	
Country × cluster FE		Y

Disasters and math scores: heterogeneity across country groups

	(1)	(2)
# of months with disasters in mid-child life		
× Pakistan	0.008	-0.001
× Bangladesh	-0.051***	-0.056***
× Other countries	0.032*	0.048***
# of months with disasters in first 1000 days of life		
× Pakistan	-0.089***	-0.069***
× Bangladesh	0.025	0.020
× Other countries	0.033*	0.034*
Observations	78305	78141
Within-country location FE	Y	
Country X cluster FE		Y

Disasters and math scores: heterogeneity across gender and age groups in Pakistan

	(1)	(2)
# of months with disaster in mid-child life		
× Male × Age 7 to 9	-0.047	-0.047
× Age 10 to 12	-0.046	-0.004
× Age 13 to 14	-0.024	-0.028
× Female × Age 7 to 9	-0.004	0.060
× Age 10 to 12	-0.098*	-0.114**
× Age 13 to 14	-0.024	-0.032
# of months with disaster in first 1000 days of life		
× Male × Age 7 to 9	-0.189***	-0.150***
× Age 10 to 12	-0.041	0.007
× Age 13 to 14	-0.049	-0.117*
× Female × Age 7 to 9	-0.233***	-0.168***
× Age 10 to 12	-0.021	0.007
× Age 13 to 14	-0.009	0.085
Observations	35854	35812
Within country location FE	Y	
Country X cluster FE		Y

Disasters and math scores: heterogeneity across gender and age groups in Bangladesh

	(1)	(2)
# of months with disaster in mid-child life		
× Male × Age 7 to 9	-0.090*	-0.076
× Age 10 to 12	0.014	0.007
× Age 13 to 14	-0.013	-0.021
× Female × Age 7 to 9	-0.151***	-0.126**
× Age 10 to 12	-0.001	0.003
× Age 13 to 14	-0.044	-0.056*
# of months with disaster in first 1000 days of life		
× Male × Age 7 to 9	0.090*	0.094*
× Age 10 to 12	0.096**	0.071
× Age 13 to 14	0.028	0.021
× Female × Age 7 to 9	0.142***	0.148***
× Age 10 to 12	0.051	-0.009
× Age 13 to 14	-0.021	0.002
Observations	22330	22300
Within country location FE	Y	
Country X cluster FE		Y