

Eskander, Shaikh; Mahmud, Minhaj Uddin

Working Paper

Health effects of climate change and mitigating effects of climate policies: Evidence from Bangladesh

ADB Economics Working Paper Series, No. 756

Provided in Cooperation with:

Asian Development Bank (ADB), Manila

Suggested Citation: Eskander, Shaikh; Mahmud, Minhaj Uddin (2024) : Health effects of climate change and mitigating effects of climate policies: Evidence from Bangladesh, ADB Economics Working Paper Series, No. 756, Asian Development Bank (ADB), Manila, <https://doi.org/10.22617/WPS240569-2>

This Version is available at:

<https://hdl.handle.net/10419/310392>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/3.0/igo/>

HEALTH EFFECTS OF CLIMATE CHANGE AND MITIGATING EFFECTS OF CLIMATE POLICIES

EVIDENCE FROM BANGLADESH

Shaikh Eskander and Minhaj Mahmud

NO. 756

December 2024

**ADB ECONOMICS
WORKING PAPER SERIES**

ADB Economics Working Paper Series

Health Effects of Climate Change and Mitigating Effects of Climate Policies: Evidence from Bangladesh

Shaikh Eskander and Minhaj Mahmud

No. 756 | December 2024

The *ADB Economics Working Paper Series* presents research in progress to elicit comments and encourage debate on development issues in Asia and the Pacific. The views expressed are those of the authors and do not necessarily reflect the views and policies of ADB or its Board of Governors or the governments they represent.

Shaikh Eskander (eskander@uab.edu) is an assistant professor at the School of Public Health, University of Alabama Birmingham and a visiting fellow at the Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science. Minhaj Mahmud (mmahmud@adb.org) is a senior economist at the Economic Research and Development Impact Department, Asian Development Bank.



Creative Commons Attribution 3.0 IGO license (CC BY 3.0 IGO)

© 2024 Asian Development Bank
6 ADB Avenue, Mandaluyong City, 1550 Metro Manila, Philippines
Tel +63 2 8632 4444; Fax +63 2 8636 2444
www.adb.org

Some rights reserved. Published in 2024.

ISSN 2313-6537 (print), 2313-6545 (PDF)
Publication Stock No. WPS240569-2
DOI: <http://dx.doi.org/10.22617/WPS240569-2>

The views expressed in this publication are those of the authors and do not necessarily reflect the views and policies of the Asian Development Bank (ADB) or its Board of Governors or the governments they represent.

ADB does not guarantee the accuracy of the data included in this publication and accepts no responsibility for any consequence of their use. The mention of specific companies or products of manufacturers does not imply that they are endorsed or recommended by ADB in preference to others of a similar nature that are not mentioned.

By making any designation of or reference to a particular territory or geographic area in this document, ADB does not intend to make any judgments as to the legal or other status of any territory or area.

This publication is available under the Creative Commons Attribution 3.0 IGO license (CC BY 3.0 IGO) <https://creativecommons.org/licenses/by/3.0/igo/>. By using the content of this publication, you agree to be bound by the terms of this license. For attribution, translations, adaptations, and permissions, please read the provisions and terms of use at <https://www.adb.org/terms-use#openaccess>.

This CC license does not apply to non-ADB copyright materials in this publication. If the material is attributed to another source, please contact the copyright owner or publisher of that source for permission to reproduce it. ADB cannot be held liable for any claims that arise as a result of your use of the material.

Please contact pubsmarketing@adb.org if you have questions or comments with respect to content, or if you wish to obtain copyright permission for your intended use that does not fall within these terms, or for permission to use the ADB logo.

Corrigenda to ADB publications may be found at <http://www.adb.org/publications/corrigenda>.

Note:

In this publication, ADB recognizes “Korea” as the Republic of Korea.

ABSTRACT

This paper explores the mitigating effects of climate policies in addressing climate-induced health adversities. We first investigate the effect of in utero exposure to rainfall variations on child health outcomes in Bangladesh and find that in utero exposure to rainfall variations negatively affects children's anthropometric outcomes. We then exploit the heterogeneity in location and timing of district-level allocations for climate projects under the Bangladesh Climate Change Trust Fund to identify that some of these rainfall-induced health adversities can be mitigated through climate policies. Our findings are robust to alternative empirical specifications and have important policy implications.

Keywords: climate change, climate finance, health, rainfall

JEL codes: Q54, Q58, I38

We gratefully acknowledge excellent research assistance from Mustafa Kamal and helpful comments and suggestions by the participants of ADB Economists Forum 2023 and Asian Economic Development Conference 2024.

1. Introduction

There is growing evidence suggesting that climate change and extreme weather events have detrimental effects on human health, lives, and livelihoods. Extreme temperature, sea-level rise, salinity, floods, storms, and droughts are some of the most common climate change-induced events (Frumkin et al. 2008, Patz et al. 2000). Available literature suggests that some climate events have a direct impact on healthcare infrastructure and thus indirect consequences on individual health. For example, several empirical papers have found extreme temperatures to predict mortality (Curriero et al. 2002; Hajat et al. 2006; Goldberg et al. 2011; Son et al. 2016; Rodrigues, Santana, and Rocha 2019) and hospitalization (Bobb et al. 2014; Schwartz, Samet, and Patz 2004; Son, Bell, and Lee 2014). The 2020 Lancet Countdown report (Watts et al. 2020) concludes that the health impacts of climate change are worsening over time with further deteriorating climate, and countries and populations with heterogeneous attributes experience those impacts disproportionately. Similarly, climate events may reduce food production and hamper food distribution to have the same detrimental effects on people's health. A systematic review of the evidence of health effects of droughts by Stanke et al. (2013), for example, reveals that droughts as a consequence of climate change can lead to adverse indirect health outcomes such as malnutrition and infectious disease. A recent study identified, *inter alia*, that there can be long-term sustained effects of climate extremes on the affected children including lower health status during adulthood (Eskander and Barbier 2022).

While the literature documenting the health effects of climate change has been growing, rigorous empirical evidence focusing on the most vulnerable countries such as Bangladesh is still very limited. Furthermore, the existing research based on secondary, high-frequency data is limited to a few developed economies since the data required for such research is available for only these countries. For example, a recent study by Guimbeau et al. (2024) focused on ocean salinity and its impact on child anthropometric measures in Bangladesh. Mullins and White (2020) found that community health centers in the United States have been successful in reducing the heat-related mortality (but not cold) by 14.2%. More recently, Nyqvist et al. (2023) showed that in Uganda, access to community healthcare centers reduced infant mortality amid adverse weather shocks. However, there is a lack of evidence on mitigating the effects of climate actions to reduce health vulnerability in such a context, which remains a lacuna for policies.¹

¹ Sustainable Development Goal 13 "Climate Action" emphasizes the need to strengthen resilience and adaptive capacity to climate-related extreme events.

In this paper, we consider the potential mitigating effects of climate finance on health adversities arising from frequent disaster exposures such as rainfall variations in the context of Bangladesh. Using three rounds of the household survey data from Bangladesh, we empirically estimate the childhood health effects of in utero exposure to rainfall variations and the mitigating effects of climate policy on these rainfall-induced health adversities. Our results first inform that in utero exposure to rainfall variations significantly reduces exposed children's anthropometric outcomes, especially their height-for-age (stunting) and weight-for-age (underweight) z scores. We then identify that climate financing projects related to adaptation and mitigation have some mitigating effects on such adversities, by improving children's anthropometric outcomes. Especially for developing economies like Bangladesh, these findings are very important since both the public and private sectors face repeated budget crises during and after a disaster and our findings, therefore, could at least be generalized to countries experiencing similar situations and impacts.

While the climate risks are universal, the tradeoff that a developing economy like Bangladesh faces requires additional attention as these harmful effects of climate change and disasters are further heightened in such a context (Intergovernmental Panel on Climate Change 2012). The scarcity, or often absence, of risk mitigation or insurance programs to protect life, property, and agricultural crops necessitates private coping strategies by the affected households. In such cases, the poorer households set their primary focus on meeting immediate subsistence needs while experiencing frequent climate events, and, therefore, may have to compromise on their preparation for facing such future climatic shocks. Climate policies such as climate legislation, action plans, and financing mechanisms adopted by governments toward risk mitigation and/or adaptation could limit the harmful effects of climate change in such a context.

Due to its geographic location and land characteristics, Bangladesh is prone to recurrent flooding and frequent tropical storm events: 26% of the population are affected by cyclones and 70% live in flood-prone regions (Cash et al. 2014). The Bangladesh Climate Change Trust Fund (BCCTF) is a national fund established in 2010 by the Government of Bangladesh to finance climate change activities in the country. It is supported by contributions from the government, international donors, and private sector organizations. The BCCTF is responsible for providing financial resources for a variety of climate change activities in Bangladesh. BCCTF supported projects such as the development of early warning systems for extreme weather events, the promotion of renewable energy sources, and the development of climate-resilient infrastructure. We exploit the heterogeneity in the location and timing of district-level allocations for climate

projects under the BCCTF to identify if rainfall-induced health adversities can be mitigated through climate policies.

The outline of this paper is as follows: Section 2 describes our data and the empirical strategy and Section 3 reports the results of the health effects of rainfall variations. Section 4 reports the results of the mitigating effects of climate policy. Finally, Section 5 concludes the paper.

2. Data and Empirical Strategy

We use three rounds of the Bangladesh Integrated Household Survey (BIHS), 2011–2012, 2015, and 2018–19, for the children’s health outcome variables. BIHS is a nationally representative rural household survey conducted by the International Food Policy Research Institute (IFPRI), details of which can be found in Ahmed (2013). Table 1 provides descriptive statistics.

Table 1: Variable Description and Summary Statistics

Variables	Description	Mean	SD	Minimum	Maximum
<i>Child’s attributes</i>					
Males	Child’s gender: 1 if male, 0 if female	0.511	0.500	0	1
Age	Child’s age in (full) months	29.50	16.84	0	60
Weight	Child’s weight in kilogram	10.51	2.941	2.100	23.70
Height	Child’s height in centimeter	82.92	13.01	45.10	110
<i>Mother’s attributes</i>					
Mother’s age	Mother’s age in (full) years	27.33	5.835	16	65
Mother’s weight	Mother’s weight in kilogram	48.26	9.094	26.90	94.30
Mother’s height	Mother’s height in centimeter	150.8	5.686	101.4	195.4
Decision making	Indicator of empowerment: 1 if females are involved in food related decisions, 0 if not	0.792	0.406	0	1
Mother’s schooling	Schooling indicator: 1 if the mother has some schooling, 0 if not	0.795	0.404	0	1
<i>Household-level attributes</i>					
Agriculture	Proportion of working-age household members working in self-employed agriculture	0.136	0.163	0	0.833
Food insecurity	Self-reported measure of extreme poverty: 1 if the household frequently suffers from hunger, 0 if not.	0.0911	0.288	0	1
Child marriage	Number of aged 18 or below currently married, widowed, divorced, or separated women in the household	0.0163	0.131	0	2
<i>Regional attributes</i>					
RWI	Relative wealth index, district level measure	-0.00453	0.356	-0.963	1.184
Crop diversification	Herfindahl–Hirschman index for value of agricultural production, district level measure	0.260	0.0381	0	0.386

Continued on the next page

Variables	Description	Mean	SD	Minimum	Maximum
Health outcomes					
HAZ	Length/height-for-age (cm)	-1.572	1.430	-10.62	8.301
WAZ	Weight-for-age (kg)	-1.436	1.123	-8.609	3.566
WHZ	Weight-for-length (kg)	-0.674	1.233	-12.10	9.057
Climate measures					
Rainfall variations	Deviation of average in utero rainfall from respective long-term average level	-3.086	35.48	-92.00	185.2
Rainfall variations T1	Deviation of average first trimester rainfall from respective long-term average level	-2.402	54.37	-236.0	404.9
Rainfall variations T2	Deviation of average second trimester rainfall from respective long-term average level	-3.349	54.61	-236.3	407.3
Rainfall variations T3	Deviation of average third trimester rainfall from respective long-term average level	-3.507	55.19	-185.9	372.3
Flood	Frequency of floods in district, 1990-2020: 0 Low (0-5), 1 Medium (6-11) or 2 High (12-18)	0: 44.06% 1: 31.45% 2: 24.49%			
Storm	Frequency of storms in district, 1990-2020: 0 Low (0-5), 1 Medium (6-11) or 2 High (12-18)	0: 44.06% 1: 39.94% 2: 16.00%			
Extreme temperature	Frequency of extreme temperature events in district, 1990-2020: 0 Low (0-4), 1 Medium (5-8) or 2 High (9-12)	0: 9.82% 1: 72.92% 2: 17.26%			
Climate policy					
BCCTF	District-level allocation under the BCCTF project, taka per capita	81.37	115.9	0	607.7
CC	BCCTF treated cohorts: 1 if the cohort is treated by BCCTF climate funds (i.e., years 2012-18), 0 if not (i.e., years 2007-11)	0.504	0.500	0	1
DD	BCCTF treated districts: 1 if the district is treated by BCCTF climate funds, 0 if not	0.850	0.357	0	1
CC2	BCCTF treated child: 1 if the child is in a treated district in treated year (i.e., CC=1 and DD=1), 0 if otherwise	0.208	0.406	0	1
No. of Obs.		6,802			

BCCTF = Bangladesh Climate Change Trust Fund, CC = child cohort, CC2 = child cohort 2, DD = district dummy, HAZ = height-for-age z-score, WAZ = weight-for-age z-score, WHZ = weight-for-length z-score.

Notes: Summary statistics are for the estimated sample of 6,802 children aged 0–60 months whose mothers were surveyed in any of the three rounds of the Bangladesh Integrated Household Survey (BIHS) data. Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

2.1. Children's Health Outcomes

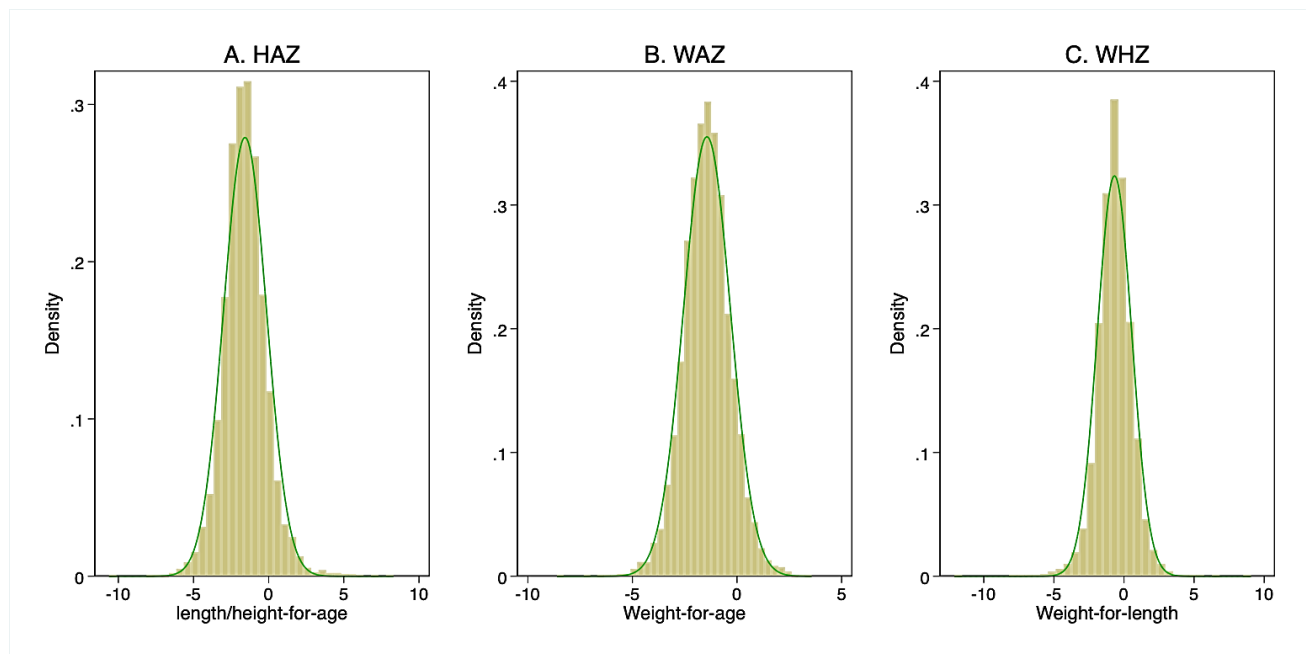
Among others, the BIHS dataset reports age, birth month, birth year, height, and weight of children aged 0-60 months whose mothers were interviewed during the three survey rounds. Complete data are available for a total of 6,802 children (3,475 males and 3,327 females), who were born between 2007 and 2018, with an average age of 29.50 months, weight of 10.51 kilograms (kg),

and height of 82.92 centimeters (cm). We use their height and weight as measured and reported by the BIHS enumerators to construct three anthropometric measures:²

- HAZ: height-for-age z-score, expressed in centimeters.
- WAZ: weight-for-age z-score, expressed in kilograms.
- WHZ: weight-for-length z-score, expressed in kilograms.

Figure 1 shows the distribution of these anthropometric measures.

Figure 1: Distribution of Anthropometry Measures



BIHS = Bangladesh Integrated Household Survey, HAZ = height-for-age z-score, IFPRI = International Food Policy Research Institute, WAZ = weight-for-age z-score, WHZ = weight-for-length z-score.

Source: Authors' calculations using the BIHS dataset (Ahmed 2013, IFPRI 2016, IFPRI 2020).

As Table 1 reports, children in our sample have an estimated average HAZ of -1.572 (with a range between -10.62 and 8.301), WAZ of -1.436 (with a range between -8.609 and 3.566), and WHZ of -0.674 (with a range between -12.10 and 9.057).

In utero period is defined as all the 9 months before the birth of a child. We use children's reported months and years of birth to calculate their respective in utero period. We also calculate first,

² To construct Z scores of child anthropometric measures, we use the Lambda Mu and Sigma (LMS) method summarizing growth standards considering the changing skewness of the distribution during childhood (Cole 1989).

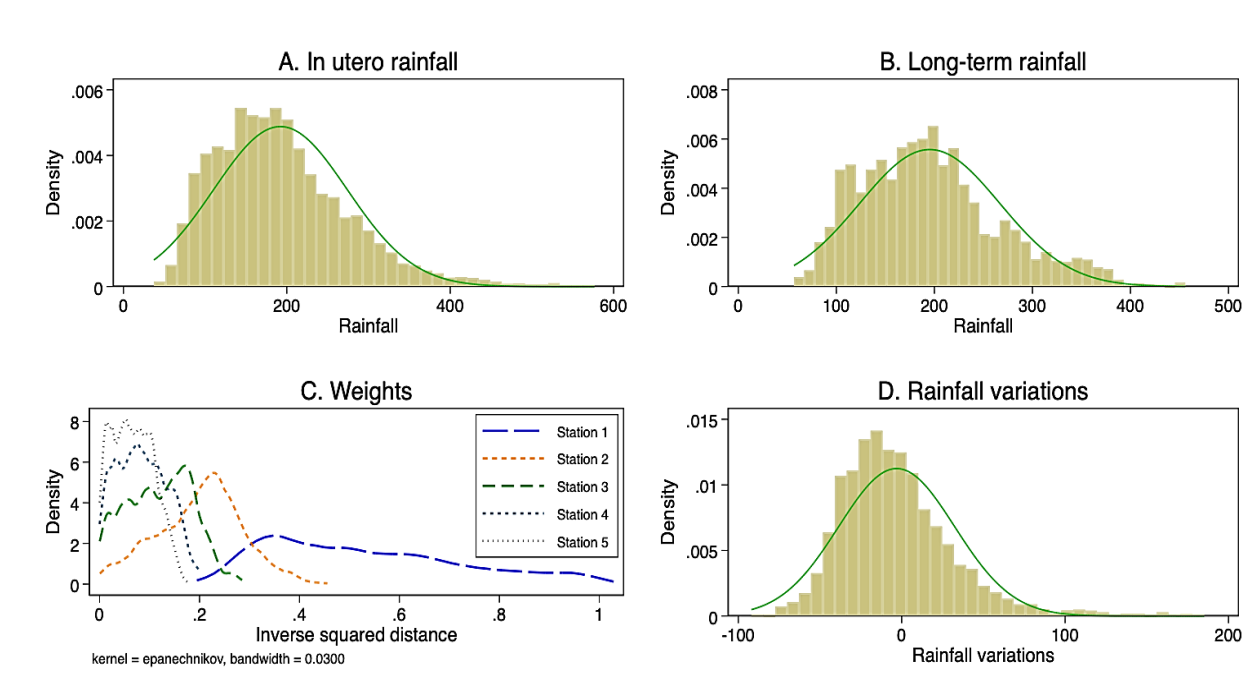
second, and third trimesters of gestation as 7–9, 4–6, and 1–3 months before childbirth, respectively.

2.2. Rainfall Variations

Weather data comes from the Bangladesh Meteorological Department (BMD), which maintains historical weather and climate data since 1950 for station-month-year level for 35 weather stations across the country.³ We calculate in utero rainfall variations by taking differences of average monthly rainfall from respective long-term average rainfall for each of the 9 months before the birth of a child and then take their average. Following related literature (e.g., Auffhammer et al. 2013; Zhang, Zhang, and Chen 2017; Guimbeau et al. 2024), we calculate the average of the rainfall data for the 5 closest stations for each household, weighing each point by the inverse of the squared distance from the household's location as reported in the BIHS dataset.⁴ The construction of the variable is reported in Appendix.

Figure 2 and Appendix Figure A1 plots the distribution of rainfall variations for our estimating sample of households.

Figure 2: Rainfall Variations



Continued on the next page

³ Bangladesh weather data is publicly available in the government website: <http://barcapps.gov.bd/climate/>.

⁴ Monthly data is not suitable for measuring temperature variations such as growing degree days (GDD) and harmful degree days (HDD). We instead control for pre-existing conditions such as agro-ecological zones and historical level of exposure to flood, storm and extreme temperatures.

Notes: Rainfall data variations are calculated as the difference of monthly rainfall from long-term average rainfall data.

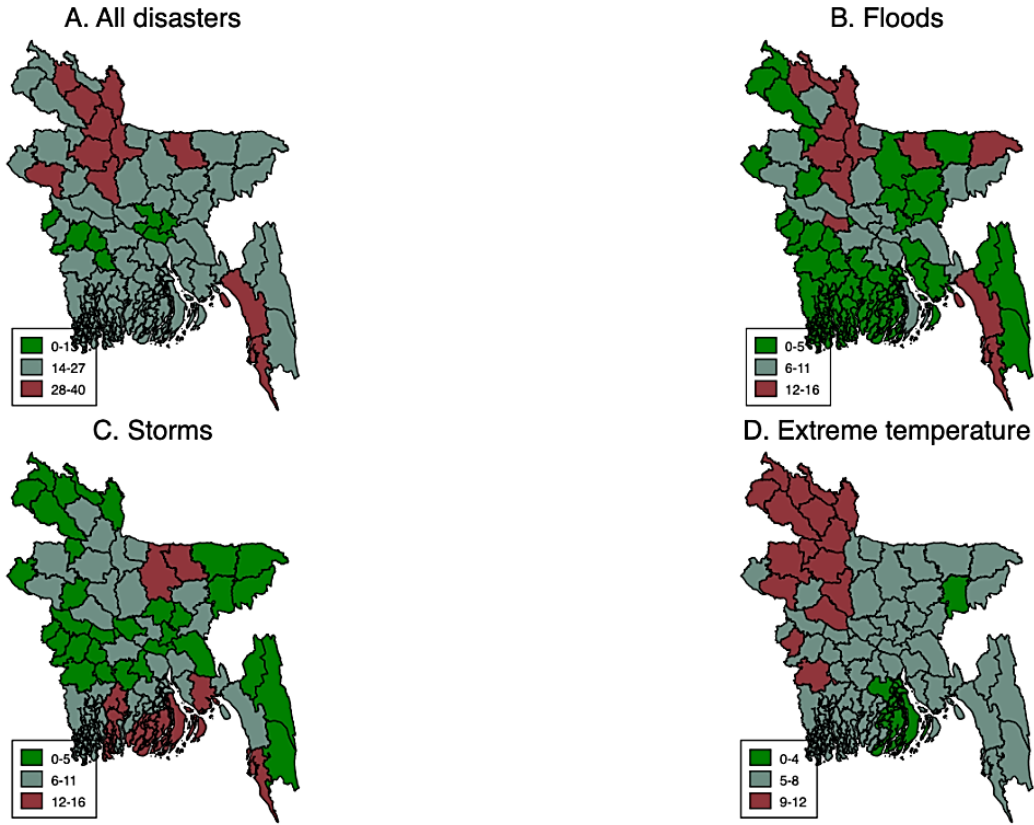
Source: Authors' calculations using the Rainfall data comes from the Bangladesh Meteorological Department (<http://barcapps.gov.bd/climate/>).

Next, occurrences of disasters vary by region in Bangladesh. For example, coastal districts in southern Bangladesh are more prone to tropical storms, while the northern districts are frequently affected by widescale flooding events. These experiences have different implications for how the households from respective regions or communities may respond to and are affected by rainfall variations. Therefore, using the EM-DAT database⁵ (EM-DAT 2022), we develop categorical measures of historical disaster exposure for each sample district. As shown in Figure 3, we consider the district-level frequency of floods and storms during 2000-2022 and categorize these districts into three groups as shown below:

	Flood (w_d^f)	Storm (w_d^s)	Extreme temperature (w_d^x)
1. Low exposure	0-5	0-5	0-4
2. Medium exposure	6-11	6-11	5-8
3. High exposure	12-18	12-18	9-12

⁵ EM-DAT. <https://public.emdat.be/> (accessed 8 January 2023).

Figure 3: Occurrences of Disasters in Bangladesh, by District, 2000–2022



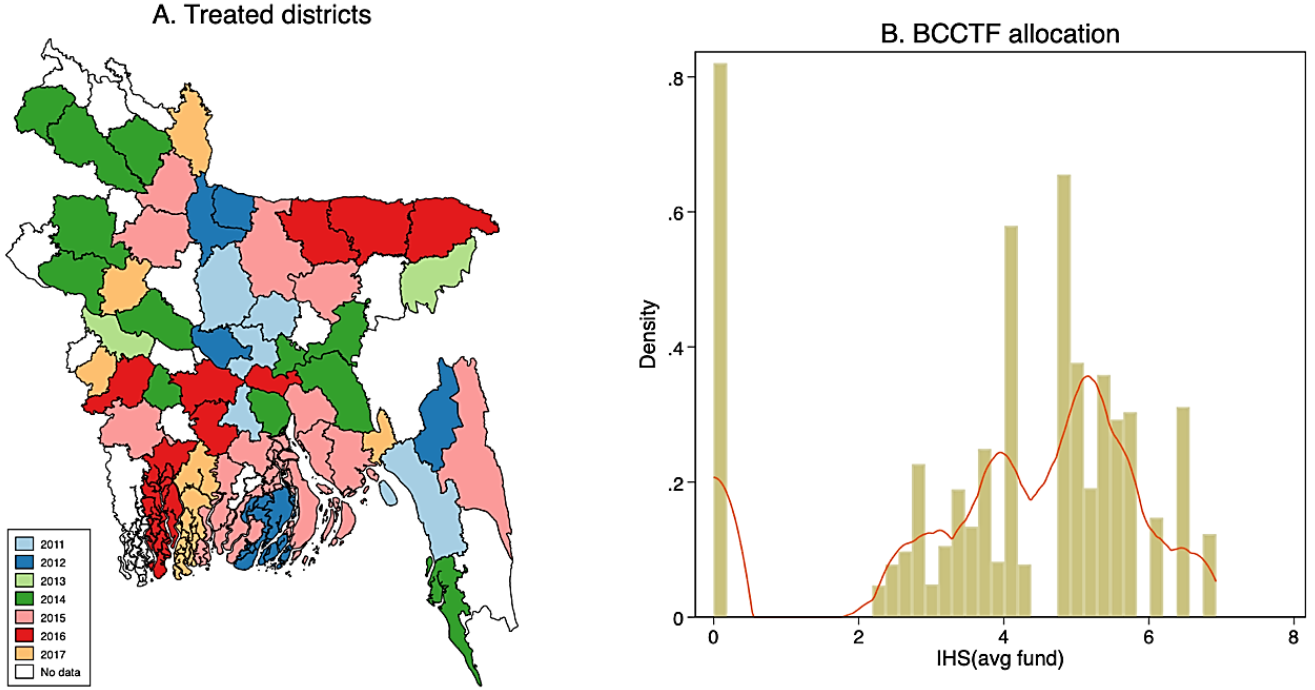
Note: The boundaries, colors, denominations, and any other information shown on this map do not imply, on the part of the Asian Development Bank, any judgment on the legal status of any territory, or any other endorsement or acceptance of such boundaries, colors, denominations, or information.

Source: Authors' calculations using the disaster data from the EM-DAT dataset (EM-DAT 2022).

2.3. Climate Policy Variable

Our climate policy variable is constructed based on district-level BCCTF allocations. As of 2022, a total of 196 projects have been completed using BCCTF funding in different districts of Bangladesh. However, since different districts have completed their respective projects in different years (Figure 4A), and thereby enter our treatment (districts receiving BCCTF allocation) in different times, it is not possible to directly assign treatment and control child cohorts and regions especially in absence of child-level panel data. Therefore, we first construct a staggered indicator of child-level climate policy treatment, T_i , which is defined as 1 if the child was born in a district that was treated before her birth (i.e., the in utero period was considered treated) and 0 if otherwise.

Figure 4: District-Level Coverage of Bangladesh Climate Change Trust Fund



Note: The boundaries, colors, denominations, and any other information shown on this map do not imply, on the part of the Asian Development Bank, any judgment on the legal status of any territory, or any other endorsement or acceptance of such boundaries, colors, denominations, or information.

Source: Authors' calculations using the Bangladesh Climate Change Trust Fund allocation data from the Government of Bangladesh website <http://www.bcct.gov.bd/>.

However, since BCCTF allocations are not uniform across districts (Appendix Figure A2), we also include a continuous measure of climate policy, F_d , which is the inverse hyperbolic sine (IHS) transformation of per-capita district-level allocation under the BCCTF project (Appendix Figure 4B). Therefore, our composite climate policy measure is given by the interaction term $T_i F_d$ where $F_d = 0$ if $T_i = 0$ and $F_d > 0$ if $T_i = 1$.

2.4. Other Variables

We also use various mother-, household- and region-level variables in the analysis. Surveyed mothers are on average 27.33 years old with an average weight of 48.26 kg and height of 150.8 cm. More than 79% of them are involved in food-related decisions in their households, while around 80% have some schooling. Most 83.3% of working-age household members work in self-employed agriculture. Moreover, around 9% of households reported frequently suffering from hunger or acute food insecurity, while there exists some prevalence of child marriage among them.

There is considerable heterogeneity across regions in terms of relative wealth and crop diversification. The relative wealth index (RWI) measures the standard of living within countries using privacy protecting connectivity data, satellite imagery, and other novel data sources (Chi et al. 2022). In Bangladesh, RWI ranges between -0.963 and 1.184 . On the other hand, we measure crop diversity in terms of a Herfindahl-Hirschman Index (HHI), which is a common measure of competitiveness. The HHI is calculated as the squared sum of the proportion of revenues from each crop so that $HHI \in (0,1)$, where $HHI \cong 0$ (i.e., lower index values) denotes high crop diversification, and $HHI \cong 1$ (i.e., higher index values) denotes low crop diversification.

2.5. Empirical Strategies

The main specific hypotheses that we test in this paper are as follows:

Hypothesis 1. Exposure to climate change and disasters reduces (child) health outcomes.

Hypothesis 2. Targeted climate finance at least partially reduces such health adversities.

Hypothesis 1 directly refers to the fetal origin hypothesis that states that in utero and neonatal exposure to adverse climatic shocks can reduce later-life health outcomes. Such adverse shocks directly affect agricultural production, livelihood, and income-earning opportunities. This could negatively impact affected households' overall food and nutrition situations, including the pregnant women in the household, resulting in lower health outcomes for (in utero) children. Therefore, we focus on children aged 0–60 months to investigate whether their in utero exposure to climatic shocks (rainfall variation) affects their physical growth.

To test for the effects of in utero weather variations on early-life health, we employ the following regression:

$$h_{idmt} = \alpha_0 + \alpha_1 c_{dmt} + X'_{idmt} \delta + \sigma_m + \lambda_t + \rho_r + \eta_{mt} + \theta_{mr} + \varphi_{tr} + \omega_d^f + \omega_d^s + \omega_d^x + \epsilon_{idmt}, \quad (1)$$

where h_{idmt} is the health outcome for child i , born in month m in year t , and whose mother was surveyed in district d . X'_{idmt} is a vector of controls and ϵ_{idmt} is the error term. We also include a full set of fixed effects to account for unobserved heterogeneities arising from month of birth (σ_m), year of birth (λ_t), agro-ecological zone (AEZ) of birth (ρ_r), month-year interaction (η_{mt}), month-AEZ interaction (θ_{mr}), and year-AEZ interaction (φ_{tr}).⁶ We also include fixed effects of district-level historical level of exposure to flood (ω_d^f), storm (ω_d^s) and extreme temperatures (ω_d^x).

⁶ Controlling for these fixed effects allow causal interpretation of our main treatment estimates (Dell et al. 2014).

Following the hypothesis 1, we are interested in the estimated coefficient of c_{dmt} , and we expect that greater (smaller) climate risk (i.e., rainfall variations) decreases (increases) health outcomes, i.e., $\hat{\alpha}_1 < 0$.

Hypothesis 2 then refers to the effects of public support aiming at mitigating the harms of climate shock considered in the paper. We focus on the 2010 BCCTF that provides the funding allocations for different climate change-related projects in Bangladesh. We investigate the mitigating effects of BCCTF on climate-induced health adversities described here. For this purpose, we employ the following regression:

$$h_{idmt} = \beta_0 + \beta_1 c_{dmt} + \beta_2 T_i + \beta_3 F_d + \beta_4 c_{dmt} T_i + \beta_5 c_{dmt} F_d + \beta_6 T_i F_d + \beta_7 c_{dmt} T_i F_d + X'_{idmt} \delta + \sigma_m + \lambda_t + \rho_r + \eta_{mt} + \theta_{mr} + \varphi_{tr} + \omega_d^f + \omega_d^s + \omega_d^x + \epsilon_{idmt}, \quad (2)$$

where h_{idmt} , c_{dmt} , X'_{idmt} and the set of fixed effects are as defined for equation (1). T_i denotes a staggered measure of climate policy instrument (defined as 1 if child i is treated by climate policy and 0 if not), whereas F_d is a measure of actual allocation of BCCTF funding (defined as the inverse hyperbolic sine transformation of district-level per-capita BCCTF allocation).

Therefore,, we are interested in the estimated coefficient of the interaction between c_{dmt} , T_i , and F_d . Following hypothesis 2, we expect that climate policies reduce climate-induced health adversities so that $\hat{\beta}_7 > 0$.

The vector of controls X'_{idmt} includes selected child-, mother-, and household-level attributes that are identified in related literature to have potential confounding effects on the health adversities of rainfall variations and the mitigating effects of climate policies. In all regression specifications, we control for the child's gender (i.e., 1 if male and 0 if female), age (in full months), and squared age. Mother-level controls include age (in full years), weight (in kg), and height (in cm) of the mother. We also control for household-level prevalence of food insecurity (i.e., 1 if the household has recently encountered an extreme poverty situation such as unavailability of food, 0 if not). We additionally control for regional crop diversity and relative wealth index.

Equations (1) and (2) include a series of temporal and spatial fixed effects to control for unobserved heterogeneity that might arise from seasonal and regional variations. In particular, month-of-birth fixed effects account for seasonal variations, whereas month- and year-of-birth fixed effects control for idiosyncratic changes that are common across survey clusters. AEZ fixed effects control for the unobserved time-invariant characteristics specific to the agroecological zone. In addition, AEZ-month fixed effects control for local seasonal variations, AE-year fixed effects control for AEZ-specific annual patterns in health outcomes, and month-year fixed effects

control for year-specific seasonal variations. Moreover, flood, storm, and extreme temperature fixed effects control for district-specific heterogeneity in the frequency of disasters.

Controlling for above-fixed effects allows us to identify the causal effects of rainfall variations on health outcomes and also the mitigating effects of climate policies on rainfall-induced health adversities (e.g., Dell et al. 2014). Parameter α_1 in equation (1) allows for differential effects of rainfall on child health outcome and we hypothesize that $\hat{\alpha}_1 < 0$. On the other hand, parameter β_7 allows for differential effects of climate policies in reducing rainfall-induced child health adversities and we hypothesize that $\hat{\beta}_7 > 0$. We assume that

$$\begin{aligned} cov(\epsilon_{idmt}, c_{dmt} | \mathcal{R}_1) &= 0 \\ cov(\epsilon_{idmt}, c_{dmt} T_i F_d | \mathcal{R}_2) &= 0' \end{aligned} \quad (3)$$

where \mathcal{R}_1 and \mathcal{R}_2 denote the set of explanatory variables in equations (1) and (2) respectively. Our identifying assumption, therefore, is the independence between the disturbances and the measure of rainfall variations, conditional on permanent differences between the districts of birth and other control variables. This implies that there are no omitted variables that could be correlated with rainfall variations, child health outcomes and climate policies. However, $\epsilon_{idmt} = \eta_{idmt} + u_i$, where u_i is the white noise error term, but η_{idmt} may be correlated across i within d . We cluster the standard errors at the sub-district or thana level to overcome this problem, which allows for village-level correlations in the error terms.

We first adopt an ordinary least squares (OLS) method to estimate equations (1) and (2). However, this is highly likely that rainfall variations are collinear with some of the fixed effects. To address this, we also employ a double-lasso variable selection strategy to select the fixed effects (e.g., Belloni et al. 2014, Guimbeau et al. 2024). This strategy first regresses the variables of interest on the full set of control variables and fixed effects to select a subset of control variables, and then regresses the outcome variable on the variables of interest and selected controls and fixed effects in the second step. The double-lasso strategy is a robust model selection framework that selects a smaller subset of control variables from all potential controls.

3. Health Effects of Rainfall Variations

Table 2 reports the health effects of rainfall variations. Panels A and B report OLS and LASSO results, respectively. Overall, all models are statistically significant, and estimated coefficients have expected signs.

Table 2: Health Effects of Rainfall Variations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	A. OLS results			B. LASSO results		
	HAZ	WAZ	WHZ	HAZ	WAZ	WHZ
Rainfall variations	-0.0022*** (0.0008)	-0.0018** (0.0007)	-0.0009 (0.0008)	-0.0015** (0.0007)	-0.0014** (0.0006)	-0.0008 (0.0007)
Males	-0.0438 (0.0373)	0.0214 (0.0295)	0.0084 (0.0322)	-0.0596* (0.0321)	0.0056 (0.0255)	-0.0012 (0.0300)
Age	-0.0913*** (0.0066)	-0.0394*** (0.0056)	0.0024 (0.0077)	-0.0912*** (0.0073)	-0.0372*** (0.0058)	0.0049 (0.0073)
Squared age	0.0013*** (0.0001)	0.0004*** (0.0001)	-0.0001 (0.0001)	0.0013*** (0.0001)	0.0004*** (0.0001)	-0.0002 (0.0001)
Food insecurity	-0.1954*** (0.0576)	-0.1800*** (0.0508)	-0.0782 (0.0567)	-0.2270*** (0.0552)	-0.1811*** (0.0443)	-0.0541 (0.0510)
Mother's age	-0.0043 (0.0038)	-0.0082*** (0.0027)	-0.0078** (0.0030)	-0.0058** (0.0030)	-0.0085*** (0.0023)	-0.0068*** (0.0026)
Mother's weight	0.0179*** (0.0021)	0.0267*** (0.0020)	0.0227*** (0.0023)	0.0178*** (0.0020)	0.0278*** (0.0016)	0.0245*** (0.0019)
Mother's height	0.0423*** (0.0036)	0.0227*** (0.0028)	-0.0050 (0.0037)	0.0421*** (0.0033)	0.0221*** (0.0025)	-0.0058* (0.0031)
Constant	-7.4281*** (0.5501)	-5.2635*** (0.4003)	-0.7633 (0.5233)			
No. of Obs.	6,760	6,760	6,760	6,802	6,802	6,802
R ²	0.2887	0.2860	0.1687			
Chi ²				680.5***	830.6***	190.6***
Birth year FE	YES	YES	YES	YES	YES	YES
Birth month FE	YES	YES	YES	YES	YES	YES
AEZ FE	YES	YES	YES	YES	YES	YES
Birth year × Birth month FE	YES	YES	YES	YES	YES	YES
Birth year × AEZ FE	YES	YES	YES	YES	YES	YES
Birth month × AEZ FE	YES	YES	YES	YES	YES	YES
Flood FE	YES	YES	YES	YES	YES	YES
Storm FE	YES	YES	YES	YES	YES	YES
Extreme Temperature FE	YES	YES	YES	YES	YES	YES

AEZ = agro-ecological zone, FE = Fixed Effects, HAZ = height-for-age z-score, LASSO = least absolute shrinkage and selection Operator, OLS = ordinary least squares, WAZ = weight-for-age z-score, WHZ = weight-for-height z-score.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in column headers. We estimate the health effects of rainfall variations using OLS (columns 1–3) and LASSO (columns 4–6) regressions according to equation (1), where our estimated coefficient of interest is given by the coefficients of the variable “Rainfall variations.” All regressions include the full set of fixed effects and control variables.

Source: Authors’ calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

We only focus on the coefficients of LASSO estimates. Column (4) shows that a one-unit increase (decrease) in in utero rainfall variations leads to 0.0015-unit decrease (increase) in HAZ. Similarly, column (5) shows that a one-unit increase (decrease) in in utero rainfall variations leads to 0.0014-unit decrease (increase) in WAZ, while column (6) shows that a one-unit increase (decrease) in in utero rainfall variations leads to 0.0008-unit decrease (increase) in WHZ.

We identify significant heterogeneity among male and female children in terms of HAZ: male children have lower HAZ than female children. In general, HAZ and WAZ indices decrease at an increasing rate with age, although the respective age coefficients are statistically insignificant for WHZ. As expected, children from food-insecure households, and those born to older mothers, have lower health status. Mother's weight has significant and positive effects on all the measures of child health status, whereas the mother's height affects HAZ and WAZ positively, but WHZ negatively.

We also conduct several robustness analyses. Appendix Table A1 also reports the results for binary health outcome variables where we define "stunted" as $HAZ < -2$, "underweight" as $WAZ < -2$, and "wasted" as $WHZ < -2$. Overall, results confirm the presence of health adversities from exposure to rainfall variations and therefore support our main results in Table 2, i.e., rainfall variations increase the probability of stunting by 0.05%, underweight by 0.05%, and wasted by 0.03%.

Our results are broadly consistent with results for a specification with trimester rainfall variations. Appendix Table A2 reports the results where we divide total in utero rainfall variations for variations during three trimesters separately. Overall, we identify that HAZ is significantly affected by the second trimester rainfall variations, whereas WAZ is significantly affected by the second and third trimester rainfall variations.

Considering the widescale use of irrigation for agriculture in Bangladesh, it is possible that negative rainfall variations may have low or zero adverse effects on agricultural outputs and therefore on health outcomes. Appendix Table A3 reports separate results for drought and flood situations that are defined as negative and positive rainfall variations, i.e., $c_{dmt} < 0$ and $c_{dmt} > 0$, respectively. As expected, we do not identify any statistically significant health adversities from rainfall variations during the drought situation. However, rainfall variations during flood situations have statistically significant negative effects on health outcomes.

Appendix Table A4 reports quantile regression results. While we still observe the significant and negative effect of rainfall variations on HAZ, there are no such adversities for WAZ anymore.

Together with our main results and results for flood situations, it is possible that WAZ effects of rainfall variations might be more profoundly felt during heavy floods that create widespread food scarcities.

3.1. Heterogenous Health Effects

Table 3 reports the results of the heterogenous impact, where we interacted indicator variables for gender, food insecurity, mother's health, and population density with rainfall variations to identify respective heterogeneity.

Table 3: Heterogenous Health Effects

Variables	(1)	(2)	(3)	Variables	(4)	(5)	(6)
	HAZ	A. Gender WAZ	WHZ		HAZ	B. Food insecurity WAZ	WHZ
Rainfall variations	-0.0017** (0.0008)	-0.0015** (0.0007)	-0.0008 (0.0008)	Rainfall variations	-0.0014* (0.0007)	-0.0013** (0.0006)	-0.0007 (0.0007)
Males	-0.0580* (0.0321)	0.0063 (0.0255)	-0.0010 (0.0300)	Food insecurity	-0.2310*** (0.0554)	-0.1879*** (0.0454)	-0.0599 (0.0520)
Rainfall variations × Males	0.0005 (0.0009)	0.0002 (0.0007)	-0.0000 (0.0008)	Rainfall variations × Food insecurity	-0.0007 (0.0017)	-0.0009 (0.0014)	-0.0006 (0.0016)
No. of Obs.	6,802	6,802	6,802	No. of Obs.	6,802	6,802	6,802
Set of FEs	YES	YES	YES	Set of FEs	YES	YES	YES
Controls	YES	YES	YES	Controls	YES	YES	YES
Chi ²	682.7***	832.0***	190.7***	Chi ²	680.5***	830.8***	190.7***
Variables	(7)	(8)	(9)	Variables	(10)	(11)	(12)
	HAZ	C. Mother's health WAZ	WHZ		HAZ	D. Population density WAZ	WHZ
Rainfall variations	-0.0009 (0.0009)	-0.0020** (0.0008)	-0.0018** (0.0009)	Rainfall variations	-0.0015* (0.0008)	-0.0014** (0.0006)	-0.0010 (0.0007)
Short	-0.4663*** (0.0454)	-0.2716*** (0.0367)	0.0098 (0.0442)	High density	0.1568*** (0.0494)	0.1360*** (0.0408)	0.0522 (0.0465)
Rainfall variations × Short	-0.0007 (0.0012)	0.0006 (0.0010)	0.0011 (0.0011)	Rainfall variations × High density	0.0013 (0.0010)	0.0010 (0.0008)	0.0007 (0.0009)
Thin	-0.3116*** (0.0471)	-0.3892*** (0.0377)	-0.2746*** (0.0446)				
Rainfall variations × Thin	-0.0003 (0.0012)	0.0021** (0.0010)	0.0031*** (0.0012)				
Short × Thin	0.0124 (0.0655)	-0.0106 (0.0526)	-0.0274 (0.0624)				
Rainfall variations × Short × Thin	-0.0003 (0.0018)	-0.0025* (0.0015)	-0.0033** (0.0017)				
No. of Obs.	6,802	6,802	6,802	No. of Obs.	6,802	6,802	6,802
Set of FEs	YES	YES	YES	Set of FEs	YES	YES	YES
Controls	YES	YES	YES	Controls	YES	YES	YES
Chi ²	622.4***	673.3***	108.5***	Chi ²	687.7***	823.3***	191.6***

FE = Fixed Effect, HAZ = height-for-age z-score, LASSO = Least Absolute Shrinkage and Selection Operator, WAZ = weight-for-age z-score, WHZ = weight-for-length z-score.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in column headers. We explore the heterogeneity in the health

Continued on the next page

effects of rainfall variations using LASSO regressions, where we extended equation (1) by introducing additional interaction terms with rainfall variations for each case in Panels A–D which provides our estimated coefficient of interest. All regressions include the full set of fixed effects and control variables. Source: Authors' calculations using the BIHS dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

Panel A reports heterogeneity impact on gender. While there are significant negative effects of rainfall variations on HAZ and WAZ and male children have significantly lower HAZ, male children having in utero exposure to rainfall variations do not have any significant additional health adversities.

Panel B reports the heterogenous impact of the household's food insecurity status. Like our main results in Table 2, these results confirm that there are significant negative effects of rainfall variations on HAZ and WAZ and food-insecure children have significantly lower HAZ and WAZ. However, we do not identify any exacerbating effects of food insecurity as the estimated coefficients of the interaction term, though negative, are statistically insignificant.

Panel C reports the heterogenous impact of the mother's health. We measure a mother's health by median height (i.e., 1 if below median height or short, 0 if above median height) and median weight (i.e., 1 if below median weight or thin, 0 if not thin or above median weight). Interestingly, the results show that children born to short mothers have significantly lower HAZ and WAZ, and children born to thin mothers have significantly lower HAZ, WAZ and WHZ. There are no additional adversities from in utero rainfall variations for children of short or thin mothers. However, while children born to short and thin mothers have similar health status, those who experienced in utero rainfall variations and born to short and thin mothers have significantly lower WAZ and WHZ.

Panel D reports heterogeneity by district-level population density per square kilometer. It is believed that regions with more facilities are inhabited by more people, and because of their proximity to big urban centers, they also receive disaster and climate risk reduction investments faster. Consistent with this narrative, our results confirm that children born in more densely populated districts have better health status. However, although positive, statistically insignificant coefficients of the interaction term inform that high density does not have any mitigating effects on rainfall-induced health adversities.

3.2. Potential Mechanisms of Health Effects

Disasters and climate events damage agricultural outputs and therefore create food shortages in affected regions. In utero exposure to such adversities therefore could affect the physical growth and development of exposed children. On the other hand, wealthier regions might have greater adaptive capacity to shocks and therefore may experience lower, if not zero, adversities. To confirm these notions, we consider relative wealth index and crop diversification as potential mechanisms behind rainfall-induced health adversities. Table 4 reports the results where we include relative wealth index and crop diversification as additional controls to see whether the estimated results vary from those in Table 2.

Table 4: Health Adversity Mechanisms

Variables	(1) Wealth Index	(2)	(3)	(4) versification	(5)	(6)
	HAZ	WAZ	WHZ	HAZ	WAZ	WHZ
Rainfall variations	-0.0016** (0.0007)	-0.0014** (0.0006)	-0.0008 (0.0007)	-0.0015** (0.0007)	-0.0013** (0.0006)	-0.0008 (0.0007)
RWI	0.1787*** (0.0493)	0.1152*** (0.0384)	0.0031 (0.0464)			
Crop diversification				-0.9222 (0.5799)	-0.3988 (0.4754)	0.1323 (0.5531)
Males	-0.0592* (0.0321)	0.0057 (0.0256)	-0.0009 (0.0301)	-0.0598* (0.0320)	0.0060 (0.0255)	-0.0024 (0.0300)
Age	-0.0921*** (0.0073)	-0.0379*** (0.0058)	0.0046 (0.0073)	-0.0915*** (0.0072)	-0.0375*** (0.0058)	0.0047 (0.0072)
Squared age	0.0013*** (0.0001)	0.0004*** (0.0001)	-0.0001 (0.0001)	0.0013*** (0.0001)	0.0004*** (0.0001)	-0.0001 (0.0001)
Food insecurity	-0.2122*** (0.0556)	-0.1764*** (0.0446)	-0.0597 (0.0513)	-0.2136*** (0.0555)	-0.1781*** (0.0445)	-0.0651 (0.0512)
Mother's age	-0.0052* (0.0030)	-0.0082*** (0.0023)	-0.0069*** (0.0026)	-0.0057* (0.0030)	-0.0087*** (0.0023)	-0.0072*** (0.0026)
Mother's weight	0.0173*** (0.0020)	0.0273*** (0.0016)	0.0242*** (0.0019)	0.0180*** (0.0020)	0.0278*** (0.0016)	0.0244*** (0.0019)
Mother's height	0.0428*** (0.0033)	0.0225*** (0.0025)	-0.0057* (0.0031)	0.0422*** (0.0033)	0.0221*** (0.0025)	-0.0060* (0.0031)
Observations	6,802	6,802	6,802	6,802	6,802	6,802
Chi ²	689.4	833.2	186.3	687.9	822.8	187.8
Birth year FE	YES	YES	YES	YES	YES	YES
Birth month FE	YES	YES	YES	YES	YES	YES
AEZ FE	YES	YES	YES	YES	YES	YES
Birth year × Birth month FE	YES	YES	YES	YES	YES	YES
Birth year × AEZ FE	YES	YES	YES	YES	YES	YES
Birth month × AEZ FE	YES	YES	YES	YES	YES	YES
Flood FE	YES	YES	YES	YES	YES	YES
Storm FE	YES	YES	YES	YES	YES	YES
Extreme Temperature FE	YES	YES	YES	YES	YES	YES

Continued on the next page

AEZ = agro-ecological Zone, FE = Fixed Effects, HAZ = height-for-age z-score, LASSO = Least Absolute Shrinkage and Selection Operator, RWI = relative wealth index, WAZ = weight-for-age z-score, WHZ = weight-for-length z-score.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in column headers. We explore the role of RWI and crop diversification as transmission mechanisms. Using LASSO regressions, we additionally include these variables in our specification in equation (1). Our estimated coefficient of interest is given by the coefficients of the variable “Rainfall variations.” All regressions include the full set of fixed effects and control variables. Source: Authors’ calculations using the Bangladesh Integrated Household Survey (BIHS) dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

Panel A reports results where we include the relative wealth index as an additional control variable. As expected, children from wealthier regions have statistically significantly higher HAZ and WAZ, and higher but insignificant WHZ.

Panel B reports results where we include regional crop diversification, a measure of agricultural diversity, as an additional control variable. Although statistically insignificant, we observe negative relationships of HAZ and WAZ with crop diversification.

3.3. Selection Issues

It is possible that the health adversities from exposure to in utero rainfall variations arise from different sources of self-selection bias. For example, male child bias, the prevalence of child marriage, and the mother’s health, entitlement, and education might influence our estimates in Table 2. For this, we collapse data to the thana-birth-year level, calculate measures for these potential sources of selection bias, and then run two-way fixed effect regressions for them on rainfall variations.

Table 5: Selection Issues

Variables	(1) Male bias	(2) Selective fertility	(3) Entitled mother	(4) Educated mother	(5) Child marriage
Rainfall variations	-0.0002 (0.0003)	0.0010 (0.0011)	-0.0002 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)
Constant	0.5107*** (0.0078)	2.6488*** (0.0013)	0.8058*** (0.0056)	0.8041*** (0.0055)	0.0433*** (0.0042)
No. of Obs.	2,569	2,569	2,569	2,569	2,569
R ²	0.1160	0.3971	0.2640	0.3156	0.1729
No. of thana	271	271	271	271	271
Set of FEs	NO	NO	NO	NO	NO
Controls	NO	NO	NO	NO	NO

FE = Fixed Effects, OLS = Ordinary Least Squares.

Continued on the next page

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in the column headers. We explore the possibilities of different selection issues by collapsing data to thana-birth-year level, and then running OLS regressions on rainfall variations. We do not include any control variables or fixed effects.

Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

Table 5 reports the results where we explore these possibilities. First, if there is a bias for male children, our results can be biased since there can be gendered differences in vulnerability to weather extremes (e.g., Arora-Jonsson 2011, Pearse 2017). To check this possibility, we run a regression for the -birth-year level average proportion of male children on average rainfall variations to see whether there is any systematic gender selection in our estimating sample. However, our estimated coefficient, reported in column (1), is statistically insignificant and therefore rules out the possibility of gender selection.

Next, women may select their fertility and decide not to give birth during weather and economic adversities. If this is the case, there will be a significantly negative relationship between rainfall variations and incidences of birth. To check this possibility, we collapse data to the thana-birth year level and count the total number of children born in a particular year in each locality. We then use this thana-birth year panel to regress the total number of children born in that year on exposure to rainfall variations. Statistically insignificant results in column (2) confirm that mothers in our estimating sample did not select their fertility decisions.

Columns (3) and (4) report results for entitlement (measured by their participation in the household's food-related decisions) and education (measured by having any schooling) of the mother. It is possible that pregnant women would receive priorities when women are involved in the household's food-related decisions and when women are educated. If this is the case, then the mother's entitlement and education should have some mitigating effects on their child's rainfall-induced health adversities, and we would have to include them in our main specifications as additional controls. To explore these possibilities, we run regressions for thana-birth-year level average entitlement and education of mothers on average rainfall variations. Estimated coefficients are statistically insignificant, and therefore, confirm that mother's entitlement and education do not necessarily have mitigating effects in our estimating sample.

Finally, rainfall variations might affect the incidence of child marriage. The extent of teen pregnancy and other related problems might be greater in regions with greater incidences of child marriage. This might bias our main results since children born to younger mothers may be more

vulnerable to climate and weather variabilities (e.g., Rylander et al. 2013). To explore this possibility, we collapse data to the thana-birth-year level and count the total number of married women aged below 18 years. We then use this thana-birth-year panel to regress total number of child marriages on rainfall variations. Statistically insignificant results confirm that there is no regional bias arising from excessive incidences of child marriage in our estimating sample.

4. Mitigating Effects of Climate Policy

4.1. Mitigating Effects of Climate Fund

We now investigate the mitigating effects of climate policy with regard to health adversities from in utero exposure to rainfall variations according to equation (2). Since we use a staggered treatment for the measure of climate policy, it is important to check for balancing property and parallel trends. First, Appendix Table A5 shows that most of the control variables have significant variations across birth year and birth district. Therefore, it is important to include the components of the vector X'_{idmt} as controls in all our regressions. Then, Appendix Table A6 shows the results for pre-treatment cohorts and untreated districts. Results for pre-treatment cohorts in Panel A show that the pre-treatment cohorts from treated districts with *in utero* exposure to rainfall variations have statistically significantly lower HAZ and WAZ. Results are statistically insignificant for untreated districts (Panel B). Together, these results imply that for any causal impact of climate policies in reducing rainfall-induced health adversities, estimated coefficients of interest must be positive and statistically significant.

Table 6 reports the mitigating effects of climate policy on health adversities from in utero exposure to rainfall variations for three anthropometry measures according to equation (2). Panels A and B report OLS and LASSO results, respectively. Overall, all models have overall statistical significance, and estimated coefficients exhibit expected directions of relationship with the respective outcome variable. Since results are similar across estimating strategies, we only describe the coefficients from LASSO regressions. We also restrict our discussion to the main coefficients of our interest.

Table 6: Mitigating Effects of Climate Policies

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	OLS results			LASSO results		
	HAZ	WAZ	WHZ	HAZ	WAZ	WHZ
Rainfall variations	-0.0020 (0.0012)	-0.0001 (0.0011)	0.0008 (0.0013)	-0.0014 (0.0013)	0.0001 (0.0010)	0.0007 (0.0011)
Treated children	0.1452 (0.2408)	-0.0956 (0.1947)	-0.2096 (0.2176)	0.1065 (0.2188)	-0.0978 (0.1632)	-0.1987 (0.1973)
Rainfall variations × Treated children	-0.0059 (0.0041)	-0.0068* (0.0037)	-0.0065 (0.0041)	-0.0059 (0.0040)	-0.0075** (0.0035)	-0.0078** (0.0037)
IHS(BCCTF)	-0.0004 (0.0153)	0.0100 (0.0115)	0.0158 (0.0118)	-0.0018 (0.0111)	0.0098 (0.0088)	0.0168* (0.0102)
Rainfall variations × IHS(BCCTF)	-0.0001 (0.0003)	-0.0005** (0.0002)	-0.0006* (0.0003)	-0.0002 (0.0003)	-0.0005** (0.0002)	-0.0005* (0.0003)
Treated children × IHS(BCCTF)	-0.0298 (0.0499)	0.0230 (0.0378)	0.0443 (0.0441)	-0.0189 (0.0424)	0.0236 (0.0328)	0.0387 (0.0393)
Rainfall variations × Treated children × IHS(BCCTF)	0.0012 (0.0009)	0.0017** (0.0008)	0.0017** (0.0008)	0.0012 (0.0008)	0.0018** (0.0007)	0.0019** (0.0008)
Males	-0.0427 (0.0374)	0.0202 (0.0297)	0.0064 (0.0324)	-0.0619* (0.0324)	0.0064 (0.0259)	0.0010 (0.0303)
Age	-0.0913*** (0.0066)	-0.0396*** (0.0056)	0.0021 (0.0077)	-0.0923*** (0.0073)	-0.0375*** (0.0058)	0.0050 (0.0073)
Squared age	0.0013*** (0.0001)	0.0004*** (0.0001)	-0.0001 (0.0001)	0.0013*** (0.0001)	0.0004*** (0.0001)	-0.0001 (0.0001)
Food insecurity	-0.1948*** (0.0577)	-0.1793*** (0.0506)	-0.0772 (0.0566)	-0.2162*** (0.0556)	-0.1782*** (0.0453)	-0.0601 (0.0517)
Mother's age	-0.0043 (0.0038)	-0.0080*** (0.0027)	-0.0075** (0.0030)	-0.0041 (0.0030)	-0.0082*** (0.0023)	-0.0078*** (0.0027)
Mother's weight	0.0179*** (0.0022)	0.0268*** (0.0020)	0.0227*** (0.0023)	0.0173*** (0.0021)	0.0274*** (0.0017)	0.0243*** (0.0020)
Mother's height	0.0423*** (0.0036)	0.0227*** (0.0028)	-0.0051 (0.0037)	0.0424*** (0.0033)	0.0223*** (0.0025)	-0.0058* (0.0031)
Constant	-7.4275*** (0.5541)	-5.3121*** (0.3970)	-0.8311 (0.5211)			
No. of Obs.	6,760	6,760	6,760	6,802	6,802	6,802
R-squared	0.2890	0.2874	0.1705			
Chi ²				662.5	805.7	196.9
Birth year FE	YES	YES	YES	YES	YES	YES
Birth month FE	YES	YES	YES	YES	YES	YES
AEZ FE	YES	YES	YES	YES	YES	YES
Birth year × Birth month FE	YES	YES	YES	YES	YES	YES
Birth year × AEZ FE	YES	YES	YES	YES	YES	YES
Birth month × AEZ FE	YES	YES	YES	YES	YES	YES
Flood FE	YES	YES	YES	YES	YES	YES
Storm FE	YES	YES	YES	YES	YES	YES
Extreme Temperature FE	YES	YES	YES	YES	YES	YES

AEZ = agro-ecological Zone, BCCTF = Bangladesh Climate Change Trust Fund, FE = Fixed Effects, HAZ = height-for-age z-score, IHS = inverse hyperbolic sine, LASSO = Least Absolute Shrinkage and Selection Operator, OLS = ordinary least squares, WAZ = weight-for-age z-score, WHZ = weight-for-height z-score.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in the column headers. We estimate the mitigating effects of climate policy on the health effects of rainfall variations according to specification (2). Our estimated coefficients of interest are given by the coefficients of the interaction term "Rainfall variations × Treated children × IHS(BCCTF)". All regressions include the full set of fixed effects and control variables.

Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

Table 6 first shows that the overall health adversities have disappeared once we introduce the climate treatments, although there are adverse health effects of in utero rainfall variations by both binary (i.e., treated children) and continuous (i.e., IHS(BCCTF)) treatments. Overall, treated children do not have any adverse health effects, but they do when exposed to in utero rainfall variations. However, our coefficient of interest is given by the coefficient of the triple interaction term “Rainfall variations \times Treated children \times IHS(BCCTF),” which is positive for all three anthropometry measures and statistically significant for HAZ and WAZ. A 1% increase in BCCTF allocation on treated children reduces the rainfall-induced health adversities, i.e., increases health status, by 0.12% in HAZ, 0.18% in WAZ and 0.19% in WHZ.

These results are broadly consistent with results for binary health outcome variables (Appendix Table A7). Overall, results confirm that a 1% increase in BCCTF allocation on treated children reduces the probability of stunting by 0.02%, underweight by 0.08% and wasted by 0.03%.

4.2. Climate Policy Mechanism Reducing Health Effects

Since health adversities are transmitted through the damages to agricultural outputs due to rainfall variations, it is important to examine whether the implemented climate policies have benefited the agricultural sector. In the absence of reliable data on agricultural outputs, we instead focus on changes in the regional share of farm employment to answer this question. For this, we collapse data to district-birth-year, thana-birth-year and union-birth-year levels, calculate average share of farm employment a for respective regional level z in birthyear t , and then employ difference-in-differences specification of the form:

$$a_{zt} = \gamma_0 + \gamma_1 C_t + \gamma_2 D_z + \gamma_3 C_t D_z + \epsilon_{zt}, \quad (4)$$

where a_{zt} denotes average share of farm employment, C_t takes the value of 1 if the cohort is treated (i.e., years 2012–2018) and 0 if not (i.e., 2007–2011), and D_z takes the value of 1 if the region is treated and 0 if not. The interaction term $C_t D_z$ yields our parameter of interest γ_3 , and we expect $\hat{\gamma}_3 > 0$, which implies a positive effect of climate policies on agricultural employment.

Table 7: Climate Policy Mechanism

Variables	(1) District-level	(2) Thana-level	(3) Union-level
Treated years	-0.1144*** (0.0158)	-0.1260*** (0.0140)	-0.1218*** (0.0120)
Treated districts	-0.0379 (0.0230)	-0.0304* (0.0169)	-0.0313* (0.0162)
Treated years × Treated districts	0.0300* (0.0179)	0.0448*** (0.0153)	0.0429*** (0.0135)
Constant	0.2169*** (0.0214)	0.2086*** (0.0157)	0.2078*** (0.0149)
No. of Obs.	754	2,569	2,837
R ²	0.2062	0.1101	0.1006
Set of FEs	NO	NO	NO
Controls	NO	NO	NO

FE = fixed effects.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variable is the average share of farm employment at region levels as identified in column headers. We estimate the effect of climate policy on agriculture by collapsing data to respective region-birthyear levels, and then running difference-in-differences regressions for the share of farm employment on climate policy treatment. Our estimated coefficients of interest are given by the coefficients of the interaction term “Treated years × Treated districts”. We do not include any control variables or fixed effects.

Source: Authors’ calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016; IFPRI 2020).

Table 7 reports the results. Overall, treated years and treated districts, separately, have a lower share of employment in agriculture. However, treated years in treated districts have a statistically significantly higher share of agricultural employment for all three regional levels. Therefore, we can assume that climate policy instruments have benefited agriculture and those benefits have then transmitted into reduced rainfall-induced health adversities.

5. Conclusions

This study contributes to the growing literature on the health effects of climate change and fills an important knowledge gap regarding the role of climate policies in addressing health vulnerabilities. We first show that *in utero* exposure to rainfall variations significantly reduces exposed children’s anthropometric outcomes, especially their height-for-age (stunting) and weight-for-age (underweight) z scores. We then identify that climate financing projects related to adaptation and mitigation do have some mitigating effects in terms of improving children’s anthropometric

outcomes. We therefore recommend more concerted efforts in allocating climate funding that can be used to reduce climate risks and consequently, climate-induced health adversities.

Climate events such as rainfall and temperature variations and extreme weather events directly affect, among others, agricultural outputs, causing hunger and malnutrition. Different initiatives undertaken by the government to help the affected people can mitigate these covariate shocks to some extent. However, due to their apparent fragility, pregnant women suffer both directly from hunger and indirectly from stresses, therefore triggering the fetal origin hypothesis that describes that *in utero* exposure to adverse environments can adversely affect later life, including childhood health outcomes. Our investigation empirically confirms this notion by identifying a significant negative impact on child height-for-age and weight-for-age z-scores outcomes. Since such adversities might remain for longer, and can result in lower adulthood human capital outcomes (e.g., Eskander and Barbier 2022), policymakers must prioritize the welfare of pregnant women and children, especially during climate and weather shocks. Moreover, since agricultural outputs are directly affected by such adverse events, helping farmers to reduce those adversities is also equally important.

Along this line, we then exploit the heterogeneity in location and timing of district-level allocations for climate projects under the BCCTF to identify that some of these rainfall-induced health adversities can be mitigated through climate policies. Combating climate change and associated harms requires directed investment toward mitigation and adaptation strategies. In this regard, our findings can be generalized for any climate-vulnerable economy, especially from the global south. Nevertheless, our paper contributes to growing literature on the adverse impact of climate change on health and the effectiveness of climate policies reducing such climate vulnerability. Our definition of climate policy is generic since disaggregated expenditures on health and agriculture are not available. We hope to address this limitation in future research.

APPENDIX

Construction of Rainfall Measures

That is, let d_{is} denotes the distance, in kilometers, between the household of a child i and a weather station s so that the respective weight W_{is} assigned to a station is given by:

$$W_{is} = \frac{1/d_{is}^2}{\sum_{k=1}^5 1/d_{ik}^2}$$

where $d_{is} \geq 0 \forall i, s$ and $\sum_{k=1}^5 1/d_{ik}^2 > 0 \forall i$. For the long-term average level of rainfall, we first take 30-year month-station average rainfall over 1990–2019, and then calculate separately household-level average rainfall \bar{R}_{is} for each of 5 closest stations (for 9 in utero months over 1990-2019). We then calculate the weighted long-term average rainfall \bar{R}_i for a child i according to:

$$\bar{R}_i = \sum_{k=1}^5 W_{is} \bar{R}_{is}$$

where $\sum_{k=1}^5 W_{is} = 1$. On the other hand, for in utero rainfall, we first calculate separate household-level average R_{is} for each of 5 closest stations over 9 in utero months, and then calculate the weighted in utero average rainfall R_i for a child i according to:

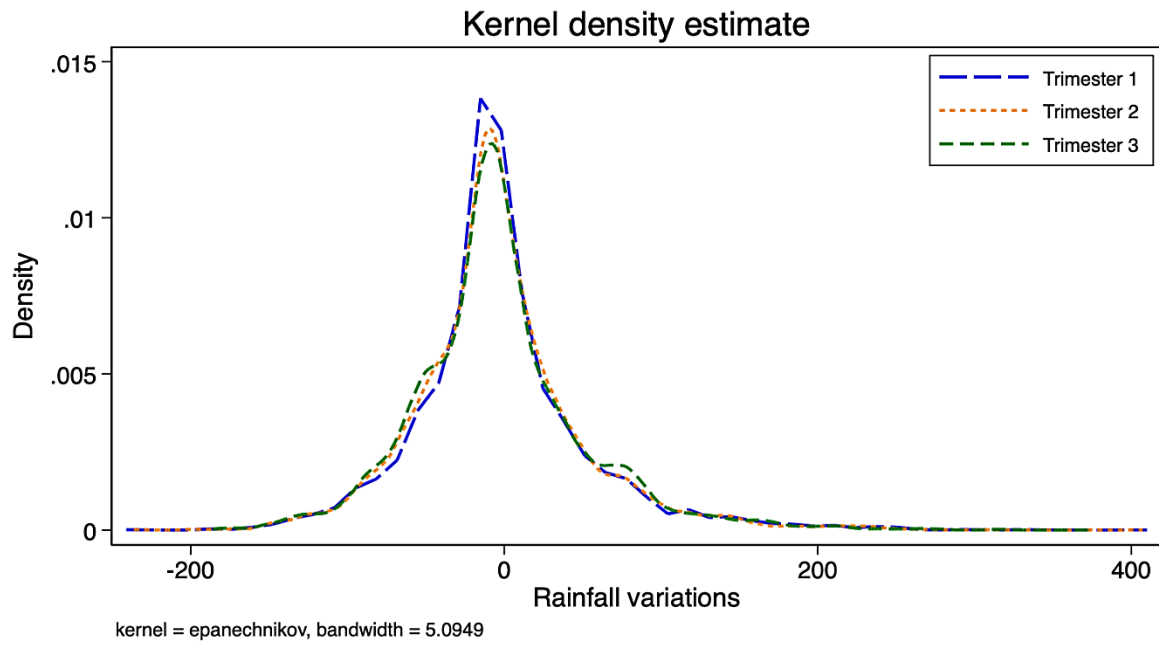
$$R_i = \sum_{k=1}^5 W_{is} R_{is}$$

where $\sum_{k=1}^5 W_{is} = 1$. Finally, rainfall variation, c_{dmt} , is defined as the difference between R_i and \bar{R}_i :

$$c_{dmt} = R_i - \bar{R}_i = \sum_{k=1}^5 W_{is} (R_{is} - \bar{R}_{is})$$

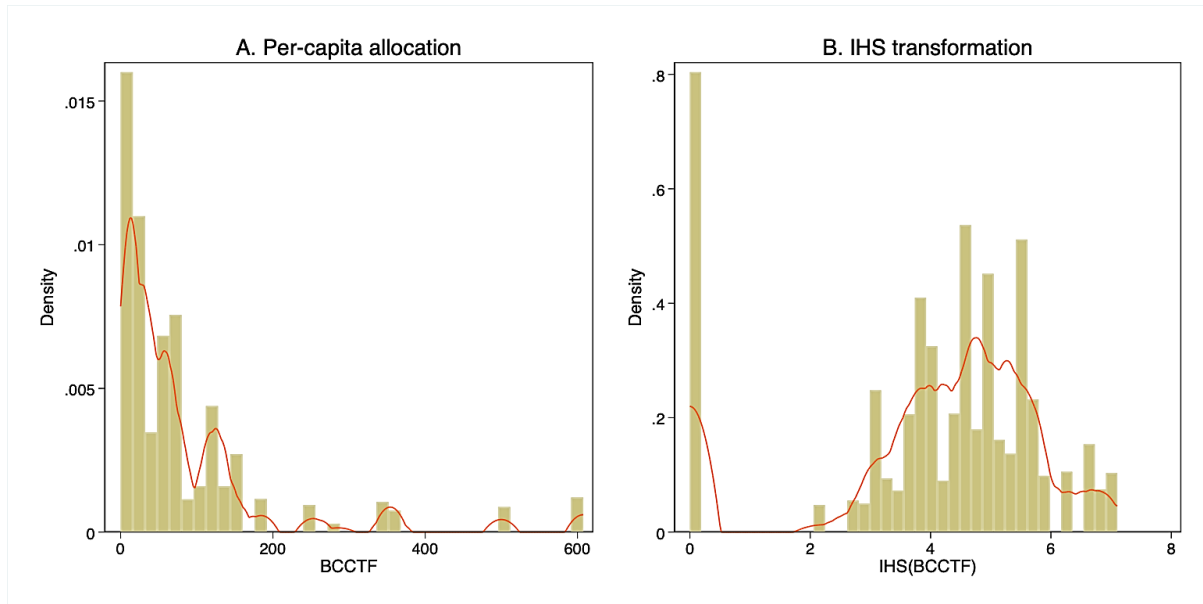
where $\sum_{k=1}^5 W_{is} = 1$. In principle, $c_{dmt} = 0$ denotes no deviation from the long-term rainfall trend, whereas $c_{dmt} > 0$ and $c_{dmt} < 0$, respectively, denote flooding and drought situations.

Figure A1: Trimester Rainfall Variations



Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

Figure A2: Bangladesh Climate Change Trust Fund Allocation



BCCTF = Bangladesh Climate Change Trust Fund.

Source: Authors' calculations using the BCCTF dataset.

Table A1: Health Effects of Rainfall Variations—Binary Outcome Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	A. OLS results			B. LASSO results		
	Stunted	Underweight	Wasted	Stunted	Underweight	Wasted
Rainfall variations	0.0007** (0.0003)	0.0007** (0.0003)	0.0002 (0.0002)	0.0005* (0.0003)	0.0005** (0.0002)	0.0003* (0.0002)
Males	0.0147 (0.0133)	-0.0170 (0.0120)	-0.0027 (0.0079)	0.0201* (0.0113)	-0.0110 (0.0108)	-0.0004 (0.0077)
Age	0.0184*** (0.0022)	0.0096*** (0.0023)	-0.0019 (0.0020)	0.0188*** (0.0023)	0.0083*** (0.0023)	-0.0020 (0.0018)
Squared age	-0.0003*** (0.0000)	-0.0001*** (0.0000)	0.0000 (0.0000)	-0.0003*** (0.0000)	-0.0001** (0.0000)	0.0000 (0.0000)
Food insecurity	0.0573*** (0.0220)	0.0781*** (0.0228)	-0.0003 (0.0148)	0.0613*** (0.0206)	0.0714*** (0.0206)	0.0005 (0.0144)
Mother's age	0.0014 (0.0012)	0.0020* (0.0011)	0.0005 (0.0007)	0.0015 (0.0010)	0.0026*** (0.0010)	0.0005 (0.0007)
Mother's weight	-0.0059*** (0.0008)	-0.0080*** (0.0008)	-0.0030*** (0.0005)	-0.0058*** (0.0007)	-0.0086*** (0.0007)	-0.0034*** (0.0005)
Mother's height	-0.0130*** (0.0012)	-0.0087*** (0.0013)	0.0003 (0.0009)	-0.0131*** (0.0011)	-0.0083*** (0.0010)	0.0006 (0.0008)
Constant	2.3294*** (0.1872)	1.7744*** (0.1737)	0.2414* (0.1314)			
No. of Obs.	6,760	6,760	6,760	6,802	6,802	6,802
R ²	0.2247	0.2093	0.1358			
Chi ²				491.1***	501.9***	75.33***
Set of FEs	YES	YES	YES	YES	YES	YES

FE = fixed effects, HAZ = height-for-age z-score, LASSO = Least Absolute Shrinkage and Selection Operator, OLS = ordinary least squares, WAZ = weight-for-age z-score, WHZ = weight-for-height z-score.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in the column headers, where stunted is defined as HAZ<-2, underweight as WAZ<-2, and wasted as WHZ<-2. We estimate the health effects of rainfall variations using OLS (columns 1–3) and LASSO (columns 4–6) regressions according to equation (1), where our estimated coefficient of interest is given by the coefficients of the variable “Rainfall variations”. All regressions include the full set of fixed effects and control variables.

Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016; IFPRI 2020).

Table A2: Health Effects of Trimester Rainfall Variations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	OLS results			LASSO results		
	HAZ	WAZ	WHZ	HAZ	WAZ	WHZ
Rainfall variations T1	-0.0009 (0.0005)	-0.0002 (0.0004)	0.0003 (0.0005)	-0.0000 (0.0004)	0.0002 (0.0003)	0.0004 (0.0004)
Rainfall variations T2	-0.0009* (0.0005)	-0.0007* (0.0004)	-0.0005 (0.0005)	-0.0008* (0.0004)	-0.0007** (0.0003)	-0.0005 (0.0004)
Rainfall variations T3	-0.0005 (0.0005)	-0.0009** (0.0004)	-0.0007 (0.0005)	-0.0006 (0.0004)	-0.0008** (0.0003)	-0.0005 (0.0004)
Males	-0.0439 (0.0373)	0.0218 (0.0295)	0.0090 (0.0322)	-0.0529 (0.0322)	0.0074 (0.0254)	-0.0041 (0.0299)
Age	-0.0913*** (0.0066)	-0.0394*** (0.0056)	0.0024 (0.0077)	-0.0891*** (0.0073)	-0.0370*** (0.0059)	0.0048 (0.0074)
Squared age	0.0013*** (0.0001)	0.0004*** (0.0001)	-0.0001 (0.0001)	0.0012*** (0.0001)	0.0004*** (0.0001)	-0.0001 (0.0001)
Food insecurity	-0.1949*** (0.0574)	-0.1811*** (0.0509)	-0.0801 (0.0570)	-0.2311*** (0.0552)	-0.1849*** (0.0444)	-0.0574 (0.0512)
Mother's age	-0.0043 (0.0038)	-0.0082*** (0.0027)	-0.0078** (0.0030)	-0.0058* (0.0030)	-0.0086*** (0.0023)	-0.0070*** (0.0026)
Mother's weight	0.0179*** (0.0021)	0.0267*** (0.0020)	0.0227*** (0.0023)	0.0179*** (0.0020)	0.0276*** (0.0016)	0.0241*** (0.0019)
Mother's height	0.0423*** (0.0036)	0.0227*** (0.0028)	-0.0051 (0.0037)	0.0421*** (0.0033)	0.0222*** (0.0025)	-0.0056* (0.0031)
Constant	-7.4250*** (0.5490)	-5.2569*** (0.4009)	-0.7513 (0.5251)			
No. of Obs.	6,760	6,760	6,760	6,802	6,802	6,802
R ²	0.2888	0.2861	0.1691			
Chi ²				670.5***	817.8***	184.8***
Birth year FE	YES	YES	YES	YES	YES	YES
Birth month FE	YES	YES	YES	YES	YES	YES
AEZ FE	YES	YES	YES	YES	YES	YES
Birth year × Birth month FE	YES	YES	YES	YES	YES	YES
Birth year × AEZ FE	YES	YES	YES	YES	YES	YES
Birth month × AEZ FE	YES	YES	YES	YES	YES	YES
Flood FE	YES	YES	YES	YES	YES	YES
Storm FE	YES	YES	YES	YES	YES	YES
Extreme Temperature FE	YES	YES	YES	YES	YES	YES

AEZ = agro-ecological zone, BCCTF = Bangladesh Climate Change Trust Fund, FE = fixed effects, HAZ = height-for-age z-score, IHS = inverse hyperbolic sine, LASSO = least absolute shrinkage and selection operator, OLS = ordinary least squares, WAZ = weight-for-age z-score, WHZ = weight-for-length z-score.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in column headers. We estimate the health effects of rainfall variations using OLS (columns 1–3) and LASSO (columns 4–6) regressions according to equation (1), where our estimated coefficient of interest is given by the coefficients of the variables “Rainfall variations T1”, “Rainfall variations T2” and “Rainfall variations T3”. All regressions include the full set of fixed effects and control variables.

Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016; IFPRI 2020).

Table A3: Health Effects During Drought and Flood Situations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Drought situation			Flood situation		
	HAZ	WAZ	WHZ	HAZ	WAZ	WHZ
Rainfall variations	0.0011 (0.0016)	0.0001 (0.0013)	-0.0008 (0.0015)	-0.0041*** (0.0012)	-0.0017* (0.0010)	0.0011 (0.0011)
Males	-0.0470 (0.0417)	0.0194 (0.0336)	0.0057 (0.0398)	-0.0734 (0.0509)	0.0081 (0.0403)	0.0102 (0.0471)
Age	-0.1004*** (0.0088)	-0.0455*** (0.0072)	0.0034 (0.0091)	-0.0761*** (0.0121)	-0.0250*** (0.0091)	0.0044 (0.0119)
Squared age	0.0014*** (0.0001)	0.0005*** (0.0001)	-0.0001 (0.0001)	0.0010*** (0.0002)	0.0002 (0.0001)	-0.0001 (0.0002)
Food insecurity	-0.1897*** (0.0724)	-0.1279** (0.0553)	-0.0118 (0.0635)	-0.3741*** (0.0873)	-0.3568*** (0.0750)	-0.1975** (0.0857)
Mother's age	-0.0011 (0.0039)	-0.0030 (0.0031)	-0.0023 (0.0035)	-0.0099** (0.0047)	-0.0151*** (0.0035)	-0.0127*** (0.0040)
Mother's weight	0.0153*** (0.0026)	0.0283*** (0.0021)	0.0271*** (0.0025)	0.0232*** (0.0032)	0.0277*** (0.0026)	0.0199*** (0.0030)
Mother's height	0.0401*** (0.0044)	0.0191*** (0.0032)	-0.0091** (0.0043)	0.0474*** (0.0048)	0.0268*** (0.0040)	-0.0029 (0.0044)
No. of Obs.	4,109	4,109	4,109	2,693	2,693	2,693
Chi ²	393.7***	489.1***	129.4***	321.3***	351.6***	66.49**
Birth year FE	YES	YES	YES	YES	YES	YES
Birth month FE	YES	YES	YES	YES	YES	YES
AEZ FE	YES	YES	YES	YES	YES	YES
Birth year × Birth month FE	YES	YES	YES	YES	YES	YES
Birth year × AEZ FE	YES	YES	YES	YES	YES	YES
Birth month × AEZ FE	YES	YES	YES	YES	YES	YES
Flood FE	YES	YES	YES	YES	YES	YES
Storm FE	YES	YES	YES	YES	YES	YES
Extreme Temperature FE	YES	YES	YES	YES	YES	YES

AEZ = agro-ecological zone, FE = fixed effects, HAZ = height-for-age z-score, IHS = inverse hyperbolic sine, LASSO = least absolute shrinkage and selection operator, OLS = ordinary least squares, WAZ = weight-for-age z-score, WHZ = weight-for-height z-score.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in the column headers. We estimate the health effects of rainfall variations using LASSO regressions according to equation (1) for drought and flood situations that are defined as negative and positive rainfall variations, i.e., $c_{dmt} < 0$ and $c_{dmt} > 0$, respectively. Our estimated coefficient of interest is given by the coefficients of the variable "Rainfall variations". All regressions include the full set of fixed effects and control variables.

Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

Table A4: Health Effects of Rainfall Variations: Quantile Regressions

Variables	(1) HAZ	(2) WAZ	(3) WHZ
Rainfall variations	-0.0010** (0.0005)	0.0001 (0.0006)	-0.0000 (0.0005)
Males	0.0998** (0.0418)	0.0000 (0.0519)	0.0690* (0.0359)
Age	-0.0146*** (0.0054)	-0.0204*** (0.0052)	-0.0229*** (0.0029)
Squared age	0.0001 (0.0001)	0.0002*** (0.0001)	0.0002*** (0.0000)
Food insecurity	-0.0136 (0.0544)	0.0138 (0.0628)	0.0462 (0.0842)
Mother's age	0.0019 (0.0047)	0.0027 (0.0029)	-0.0011 (0.0036)
Mother's weight	-0.0033 (0.0033)	-0.0011 (0.0020)	0.0015 (0.0024)
Mother's height	0.0029 (0.0046)	0.0044 (0.0028)	-0.0001 (0.0036)
Constant	1.4330** (0.6831)	0.9430** (0.4261)	1.7823*** (0.5297)
No. of Obs.	6,802	6,802	6,802
Set of FEs	NO	NO	NO

FE = fixed effects, HAZ = height-for-age z-score, WAZ = weight-for-age z-score, WHZ = weight-for-height z-score.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in the column headers. Quantile regressions follow the specification (1) excluding the fixed effects. Our estimated coefficient of interest is given by the coefficients of the variable "Rainfall variations".

Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

Table A5: Balancing Properties

Variables	(1) CC 0 DD 0	(2) CC 0 DD 1	(3) CC 1 DD 0	(4) CC 1 DD 1	(5) (2) – (1)	(6) (3) – (1)	(7) (4) – (1)
Males	0.526 (0.500)	0.496 (0.500)	0.496 (0.501)	0.525 (0.499)	-0.0299	-0.0298	-0.0006
Age	34.25 (16.93)	33.57 (17.20)	25.48 (15.37)	25.37 (15.47)	-0.6814	-8.7756***	-8.8840***
Weight	11.03 (2.901)	10.93 (2.965)	10.07 (2.844)	10.09 (2.869)	-0.0922	-0.952***	-0.936***
Height	85.56 (12.78)	84.91 (13.18)	80.89 (12.46)	80.86 (12.59)	-0.6495	-4.6717***	-4.6951***
Mother's age	27.10 (5.941)	27.73 (5.973)	27.33 (5.537)	26.99 (5.707)	0.6328**	0.2304	-0.1047
Mother's weight	46.76 (8.460)	46.78 (8.490)	49.65 (9.562)	49.72 (9.416)	0.0271	2.8970***	2.9660***
Mother's height	150.3 (5.216)	150.6 (5.886)	150.7 (5.608)	151.0 (5.577)	0.3101	0.4348	0.7184***
Decision making	0.687 (0.464)	0.722 (0.448)	0.845 (0.363)	0.871 (0.336)	0.0356*	0.1577***	0.1838***
Mother's schooling	0.705 (0.456)	0.732 (0.443)	0.853 (0.355)	0.862 (0.344)	0.0268	0.1478***	0.1573***
Agriculture	0.201 (0.193)	0.175 (0.178)	0.0841 (0.123)	0.0950 (0.131)	-0.0259***	-0.1170***	-0.1060***
Food insecurity	0.101 (0.301)	0.118 (0.323)	0.0714 (0.258)	0.0667 (0.250)	0.0174	-0.0293*	-0.0340***
Child marriage	0.00549 (0.0740)	0.00530 (0.0774)	0.0294 (0.181)	0.0268 (0.166)	-0.0002	0.0239***	0.0213***
RWI	-0.0382 (0.355)	-0.00870 (0.355)	-0.0414 (0.370)	0.0116 (0.354)	0.0295*	-0.0032	0.0499***
Crop diversification	0.246 (0.0355)	0.261 (0.0377)	0.249 (0.0405)	0.262 (0.0377)	0.0154	0.0034	-0.0161***
HAZ	-1.824 (1.386)	-1.820 (1.397)	-1.394 (1.280)	-1.317 (1.443)	0.0043	0.4301***	0.5065***
WAZ	-1.644 (1.100)	-1.607 (1.099)	-1.320 (1.061)	-1.252 (1.128)	0.0377	0.3242	0.3920***
WHZ	-0.742 (1.193)	-0.679 (1.196)	-0.678 (1.119)	-0.657 (1.290)	0.0631	0.0644	0.0856
No. of Obs.	546	2,828	476	2,952			

BCCTF = Bangladesh Climate Change Trust Fund, HAZ = height-for-age z-score, IHS = inverse hyperbolic sine, OLS = ordinary least squares, RWI = relative wealth index, WAZ = weight-for-age z-score, WHZ = weight-for-height z-score.

Notes: Balancing properties are for the estimating sample of 6,802 children aged 0–60 months whose mothers were surveyed in any of the three rounds of the Bangladesh Integrated Household Survey (BIHS) data. CC denotes BCCTF-treated cohorts, i.e., 1 if the cohort is treated by BCCTF climate funds (i.e., years 2012–2018), 0 if not (i.e., years 2007–2011), whereas DD denotes BCCTF treated districts, i.e., 1 if the district is treated by BCCTF climate funds, 0 if not.

Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI 2016], IFPRI 2020).

Table A6: Parallel Trends

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-treatment cohorts			Untreated districts		
	HAZ	WAZ	WHZ	HAZ	WAZ	WHZ
Rainfall variations	0.0019 (0.0020)	0.0026 (0.0016)	0.0019 (0.0018)	0.0019 (0.0020)	0.0026 (0.0016)	0.0019 (0.0018)
Treated districts	-0.0237 (0.0829)	0.0026 (0.0579)	0.0454 (0.0614)			
Rainfall variations × Treated districts	-0.0045** (0.0022)	-0.0056*** (0.0018)	-0.0029 (0.0020)			
Treated cohorts				0.4217*** (0.0870)	0.3058*** (0.0650)	0.0491 (0.0615)
Rainfall variations × Treated cohorts				-0.0038 (0.0027)	-0.0010 (0.0021)	0.0006 (0.0023)
Constant	-1.8123*** (0.0758)	-1.6283*** (0.0510)	-0.7310*** (0.0544)	-1.8123*** (0.0767)	-1.6283*** (0.0516)	-0.7310*** (0.0550)
No. of Obs.	3,374	3,374	3,374	1,022	1,022	1,022
R ²	0.0026	0.0060	0.0012	0.0274	0.0258	0.0051
Set of FEs	NO	NO	NO	NO	NO	NO
Controls	NO	NO	NO	NO	NO	NO

FE = fixed effects, HAZ = height-for-age z-score, WAZ = weight-for-age z-score, WHZ = weight-for-height z-score.

Notes: Robust standard errors in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in the column headers. The estimated sample is restricted to the untreated households only, therefore providing a test for parallel trend assumption.

Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016; IFPRI 2020).

Table A7: Mitigating Effects of Climate Policies: Binary Outcome Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Stunted	Underweight	Wasted	Stunted	Underweight	Wasted
Rainfall variations	0.0007 (0.0005)	0.0002 (0.0005)	-0.0001 (0.0003)	0.0005 (0.0005)	0.0000 (0.0004)	0.0000 (0.0003)
Treated children	-0.0050 (0.0740)	-0.0340 (0.0720)	0.0206 (0.0459)	-0.0097 (0.0694)	0.0019 (0.0623)	0.0093 (0.0502)
Rainfall variations × Treated children	0.0011 (0.0014)	0.0030** (0.0013)	0.0017 (0.0011)	0.0014 (0.0015)	0.0035** (0.0014)	0.0017 (0.0011)
IHS(BCCTF)	-0.0058 (0.0051)	-0.0060 (0.0041)	-0.0022 (0.0028)	-0.0044 (0.0040)	-0.0044 (0.0039)	-0.0017 (0.0026)
Rainfall variations × IHS(BCCTF)	-0.0000 (0.0001)	0.0002 (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)	0.0002* (0.0001)	0.0001 (0.0001)
Treated children × IHS(BCCTF)	0.0087 (0.0160)	0.0146 (0.0139)	0.0006 (0.0094)	0.0074 (0.0139)	0.0067 (0.0125)	0.0018 (0.0099)
Rainfall variations × Treated children × IHS(BCCTF)	-0.0002 (0.0003)	-0.0006** (0.0003)	-0.0003 (0.0002)	-0.0002 (0.0003)	-0.0008*** (0.0003)	-0.0003 (0.0002)
Males	0.0146 (0.0134)	-0.0169 (0.0121)	-0.0026 (0.0079)	0.0194* (0.0115)	-0.0118 (0.0110)	-0.0010 (0.0078)
Age	0.0184*** (0.0022)	0.0098*** (0.0023)	-0.0019 (0.0020)	0.0189*** (0.0023)	0.0083*** (0.0023)	-0.0021 (0.0018)
Squared age	-0.0003*** (0.0000)	-0.0001*** (0.0000)	0.0000 (0.0000)	-0.0003*** (0.0000)	-0.0001** (0.0000)	0.0000 (0.0000)
Food insecurity	0.0568** (0.0220)	0.0773*** (0.0227)	-0.0008 (0.0148)	0.0585*** (0.0208)	0.0699*** (0.0209)	-0.0030 (0.0143)
Mother's age	0.0015 (0.0012)	0.0021* (0.0011)	0.0005 (0.0007)	0.0014 (0.0010)	0.0023** (0.0010)	0.0007 (0.0007)
Mother's weight	-0.0059*** (0.0008)	-0.0080*** (0.0008)	-0.0030*** (0.0005)	-0.0058*** (0.0007)	-0.0083*** (0.0007)	-0.0034*** (0.0005)
Mother's height	-0.0129*** (0.0012)	-0.0086*** (0.0013)	0.0003 (0.0009)	-0.0131*** (0.0011)	-0.0086*** (0.0010)	0.0006 (0.0008)
Constant	2.3373*** (0.1898)	1.7869*** (0.1728)	0.2422* (0.1305)			
No. of Obs.	6,760	6,760	6,760	6,802	6,802	6,802
R ²	0.2252	0.2107	0.1367			
Chi ²				480.7***	489.5***	76.05**
Set of FEs	YES	YES	YES	YES	YES	YES

BCCTF = Bangladesh Climate Change Trust Fund, FE = fixed effects, HAZ = height-for-age z-score, IHS = inverse hyperbolic sine, LASSO = least absolute shrinkage and selection operator, OLS = ordinary least squares, WAZ = weight-for-age z-score, WHZ = weight-for-height z-score.

Notes: Robust standard errors clustered at thana level in parentheses. ***, **, and * represent statistical significance at 1-, 5-, and 10-percent levels, respectively. All variables follow their respective definitions in Table 1. Dependent variables are reported in the column headers, where stunted is defined as HAZ<-2, underweight as WAZ<-2, and wasted as WHZ<-2. We estimate the mitigating effects of climate policy on the health effects of rainfall variations using OLS (columns 1–3) and LASSO (columns 4–6) regressions according to equation (2). Our estimated coefficients of interest are given by the coefficients of the interaction term “Rainfall variations × Treated children × IHS(BCCTF)”. All regressions include the full set of fixed effects and control variables.

Source: Authors' calculations using the Bangladesh Integrated Household Survey dataset (Ahmed 2013, International Food Policy Research Institute [IFPRI] 2016, IFPRI 2020).

REFERENCES

- Adélaïde, Lucie, Olivier Chanel, and Mathilde Pascal. 2022. "Health Effects from Heat Waves in France: An Economic Evaluation." *The European Journal of Health Economics*, 23 (1): 119–31.
- Ahmed, Akhter. 2013. "Bangladesh Integrated Household Survey (BIHS) 2011-2012", <https://doi.org/10.7910/DVN/OR6MHT>, Harvard Dataverse, V5.
- Arora-Jonsson, Seema. 2011. "Virtue and Vulnerability: Discourses on Women, Gender and Climate Change." *Global Environmental Change*, 21 (2): 744–51.
- Auffhammer, M., Hsiang, S.M., Schlenker, W. and Sobel, A. 2013. "Using Weather Data and Climate Model Output in Economic Analyses of Climate Change." *Review of Environmental Economics and Policy*, 7 (2): 181–98
- Barreca, Alan, Karen Clay, Olivier Deschênes, Michael Greenstone, and Joseph S. Shapiro. 2016. "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century." *Journal of Political Economy*, 124 (1): 105–59.
- Barreca, Alan I. 2012. Climate Change, Humidity, and Mortality in the United States. *Journal of Environmental Economics and Management*, 63 (1): 19–34.
- Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. 2014. "Inference on Treatment Effects After Selection Among High-Dimensional Controls." *The Review of Economic Studies*, 81 (2): 608–50.
- Bobb, Jennifer F., Ziad Obermeyer, Yun Wang, and Francesca Dominici. 2014. "Cause-Specific Risk of Hospital Admission Related to Extreme Heat in Older Adults." *JAMA* 312 (24): 2659–67.
- Cash, Richard A., Shantana R. Halder, Mushtuq Husain, Md Sirajul Islam, Fuad H. Mallick, Maria A. May, Mahmudur Rahman, and M. Aminur Rahman. 2014. "Reducing the Health Effect of Natural Hazards in Bangladesh." *The Lancet*, 382 (9910): 2094–103.
- Chi, Guangha, Han Fang, Sourav Chatterjee, and Joshua E. Blumenstock. 2022. "Micro Estimates of Wealth for All Low-and Middle-Income Countries." *Proceedings of the National Academy of Sciences*, 119 (3): p.e2113658119.
- Cole, T.J., 1989. "Using the LMS Method to Measure Skewness in the NCHS and Dutch National Height Standards." *Ann Hum Biol.* 1989 Sep–Oct; 16 (5): 407–19.
- Curriero, Frank C., Karlyn S. Heiner, Jonathan M. Samet, Scott L. Zeger, Lisa Strug, and Jonathan A. Patz. 2002. "Temperature and Mortality in 11 Cities of the Eastern United States." *American Journal of Epidemiology*, 155 (1): 80–87.
- Das, Debasish Kumar, Md Sariful Islam, Sheikh Hadiujjaman, Champa Bati Dutta, and Md Manjur Morshed. 2019. "Health Cost of Salinity Contamination in Drinking Water: Evidence from Bangladesh." *Environmental Economics and Policy Studies* 21 (3): 371–97.

- Deschênes, O. and Greenstone, M., 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics*, 3 (4): 152–85.
- Deschênes, Olivier, and Enrico Moretti. 2009. "Extreme Weather Events, Mortality, and Migration." *The Review of Economics and Statistics*, 91 (4): 659–81.
- Deschênes, Olivier, Michael Greenstone, and Jonathan Guryan. 2009. "Climate Change and Birth Weight." *American Economic Review*, 99 (2): 211–7.
- Deschênes, Olivier. 2022. "The Impact of Climate Change on Mortality in the United States: Benefits and Costs of Adaptation." *Canadian Journal of Economics*, 55 (3):1227–49.
- EM-DAT, C.R.E.D. 2020. The OFDA/CRED International Disaster Database. *Université Catholique*.
- Eskander, Shaikh M., and Edward B. Barbier. 2022. "Long-Term Impacts of the 1970 Cyclone in Bangladesh." *World Development*, 152, 105793.
- Frumkin, Howard, Jeremy Hess, George Luber, Josephine Malilay, and Michael McGeehin. 2008. "Climate Change: The Public Health Response." *American Journal of Public Health*, 98 (3): 435–45.
- Goldberg, Mark S., Antonio Gasparrini, Ben Armstrong, and Marie-France Valois. 2011. "The Short-Term Influence of Temperature on Daily Mortality in the Temperate Climate of Montreal, Canada." *Environ Res*, 111 (6): 853–60.
- Guimbeau, Amanda, Xinde Ji, Nidhiya Menon, and Zi Long. 2024. "Ocean salinity, early-life health, and adaptation." *Journal of Environmental Economics and Management*, 125: 102954.
- Haines, Andy, and Jonathan A. Patz. 2004. "Health Effects of Climate Change." *Jama*, 291 (1): 99–103.
- Hajat, Shakoar, Ben Armstrong, Michela Baccini, Annibale Biggeri, Luigi Bisanti, Antonio Russo, Anna Paldy, Bettina Menne, and Tom Kosatsky. 2006. "Impact of High Temperatures on Mortality: Is There an Added Heat Wave Effect?" *Epidemiology*, 17 (6): 632–8.
- Hübler, Michael, Gernot Klepper, and Sonja Peterson. 2008. "Costs of Climate Change: The Effects of Rising Temperatures on Health and Productivity in Germany." *Ecological Economics*, 68 (1): 381–93.
- IFPRI. 2016. "Bangladesh Integrated Household Survey (BIHS) 2015." <https://doi.org/10.7910/DVN/BXSYEL>, Harvard Dataverse, V4.
- IFPRI. 2020. "Bangladesh Integrated Household Survey (BIHS) 2018–2019." <https://doi.org/10.7910/DVN/NXKLZJ>, Harvard Dataverse, V2.
- Intergovernmental Panel on Climate Change. 2012. Summary for Policymakers. In [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. *Managing the Risks of*

Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press.

- Karlsson, Martin and Nicolas R. Ziebarth. 2018. "Population Health Effects and Health-Related Costs of Extreme Temperatures: Comprehensive Evidence from Germany." *Journal of Environmental Economics and Management*, 91: 93–117.
- Khan, Aneire E., Andrew Ireson, Sari Kovats, Sontosh Kumar Mojumder, Amirul Khusru, Atiq Rahman, and Paolo Vineis. 2011. "Drinking Water Salinity and Maternal Health in Coastal Bangladesh: Implications of Climate Change." *Environmental Health Perspectives*, 119 (9): 1328–32.
- Khan, Aneire E., Wei W. Xun, Habibul Ahsan, and Paolo Vineis. "Climate change, sea-level rise, and health impacts in Bangladesh." *Environment: Science and Policy for Sustainable Development* 53, 5 (2011): 18–33.
- Lake, I. R., and G. C. Barker. 2018. "Climate Change, Foodborne Pathogens and Illness in Higher-Income Countries." *Curr Environ Health Rep* 5 (1): 187–96. doi: 10.1007/s40572-018-0189-9.
- Levy, Karen, Shanon M. Smith, and Elizabeth J. Carlton. 2018. "Climate Change Impacts on Waterborne Diseases: Moving Toward Designing Interventions." *Current Environmental Health Reports*, 5 (2): 272–282.
- McMichael, A. J., R. E. Woodruff, and S. Hales. 2006. "Climate Change and Human Health: Present and Future Risks." *Lancet*, 367 (9513): 859–69.
- McMichael, Anthony J, Rosalie Woodruff, Peter Whetton, Kevin Hennessy, Neville Nicholls, Simon Hales, Alistair Woodward, and Tord Kjellstrom. 2003. "Human Health and Climate Change in Oceania: A Risk Assessment." *Canberra: Commonwealth Department of Health and Ageing*, 45.
- Mullins, J. T. and C. White. 2020. "Can Access to Health Care Mitigate the Effects of Temperature on Mortality?" *Journal of Public Economics*, 191.
- Nelson, Deborah Imel. "Health Impact Assessment of Climate Change in Bangladesh." *Environmental Impact Assessment Review*, 23 (3): 323–41.
- Nyqvist, B., von Carnap, M.T., Guariso, A., and J. Svensson. 2023. "Weather Shocks, Child Mortality, and Adaptation: Experimental Evidence from Uganda." *CEPR Discussion Paper No. 18373*. CEPR Press, Paris and London.
- Patz, J. A., D. Engelberg, and J. Last. 2000. "The Effects of Changing Weather on Public Health." *Annual Review of Public Health*, 21: 271–307.
- Pearse, R. 2017. "Gender and Climate Change." *Wiley Interdisciplinary Reviews: Climate Change*, 8 (2): e451.
- Pestel, Nico and Florian Wozny. 2021. "Health Effects of Low Emission Zones: Evidence from German Hospitals." *Journal of Environmental Economics and Management*, 109: 102512.

- Pingali, Prabhu, Anaka Aiyar, Mathew Abraham, and Andaleeb Rahman. 2019. "Managing Climate Change Risks in Food Systems." In *Transforming food systems for a rising India*, 241–75. Springer.
- Rahman, Mohammed M., Sate Ahmad, Ayesha S. Mahmud, Md Hassan-uz-Zaman, Mahin A. Nahian, Ali Ahmed, Quamrun Nahar, and Peter K. Streatfield. 2019. "Health Consequences of Climate Change in Bangladesh: An Overview of the Evidence, Knowledge Gaps and Challenges." *Wiley Interdisciplinary Reviews: Climate Change*, 10 (5): e601.
- Rocque, Rhea J., Caroline Beaudoin, Ruth Ndjaboue, Laura Cameron, Louann Poirier-Bergeron, Rose-Alice Poulin-Rheault, Catherine Fallon, Andrea C. Tricco, and Holly O. Witteman. 2016. "Health Effects of Climate Change: An Overview of Systematic Reviews." *BMJ Open*, 11 (6): e046333.
- Rodrigues, Mónica, Paula Santana, and Alfredo Rocha. 2019. "Effects of Extreme Temperatures on Cerebrovascular Mortality in Lisbon: A Distributed Lag Non-linear Model." *International Journal of Biometeorology*, 63 (4): 549–59.
- Rylander, C., Øyvind Odland, J. and Manning Sandanger, T., 2013. "Climate Change and the Potential Effects on Maternal and Pregnancy Outcomes: An Assessment of the Most Vulnerable—the Mother, Fetus, and Newborn Child." *Global Health Action*, 6 (1): 19538.
- Schwartz, Joel, Jonathan M. Samet, and Jonathan A. Patz. 2004. "Hospital Admissions for Heart Disease: The Effects of Temperature and Humidity." *Epidemiology*, 15 (6): 755–61.
- Son, Ji-Young, Michelle L. Bell, and Jong-Tae Lee. 2014. "The Impact of Heat, Cold, and Heat Waves on Hospital Admissions in Eight Cities in Korea." *International Journal of Biometeorology*, 58 (9): 1893–903.
- Son, Ji-Young, N. Gouveia, M. A. Bravo, C. U. de Freitas, and M. L. Bell. 2016. "The Impact of Temperature on Mortality in a Subtropical City: Effects of Cold, Heat, and Heat Waves in São Paulo, Brazil." *International Journal of Biometeorology*, 60 (1): 113–21.
- Stanke, Carla, Marko Kerac, Christel Prudhomme, Jolyon Medlock, and Virginia Murray. 2013. "Health Effects of Drought: A Systematic Review of the Evidence." *PLoS Currents*, 5.
- Watts, N., Amann, M., Arnell, N., Ayeb-Karlsson, S., Beagley, J., Belesova, K., Boykoff, M., Byass, P., Cai, W., Campbell-Lendrum, D. and Capstick, S. 2021. "The 2020 Report of the Lancet Countdown on Health and Climate Change: Responding to Converging Crises." *The Lancet*, 397 (10269): 129–70.
- White, C., 2017. "The Dynamic Relationship Between Temperature and Morbidity." *Journal of the Association of Environmental and Resource Economists*, 4 (4): 1155–98.
- World Health Organization (WHO). 2006. WHO Child Growth Standards: Length/height-for-age, weight-for-age, weight-for-length, weight-for-height and body mass index-for-age: Methods and development.

- WHO. 2007. WHO Child Growth Standards: Head circumference-for-age, arm circumference-for-age, triceps skinfold-for-age and subscapular skinfold-for-age: Methods and Development. Geneva: World Health Organization.
- Zhang, P., Zhang, J. and Chen, M., 2017. "Economic Impacts of Climate Change on Agriculture: The Importance of Additional Climatic Variables Other than Temperature and Precipitation." *Journal of Environmental Economics and Management*, 83: 8–31.

Health Effects of Climate Change and Mitigating Effects of Climate Policies

Evidence from Bangladesh

This paper explores the mitigating effects of climate policies in addressing climate-induced health adversities. It investigates the effect of in utero exposure to rainfall variations on child health in Bangladesh, finding negative effects on children's anthropometric outcomes. It exploits the heterogeneity in location and timing of district-level allocations for climate projects under the Bangladesh Climate Change Trust Fund to identify that some of these rainfall-induced health adversities can be mitigated through climate policies.

About the Asian Development Bank

ADB is committed to achieving a prosperous, inclusive, resilient, and sustainable Asia and the Pacific, while sustaining its efforts to eradicate extreme poverty. Established in 1966, it is owned by 69 members—49 from the region. Its main instruments for helping its developing member countries are policy dialogue, loans, equity investments, guarantees, grants, and technical assistance.



ASIAN DEVELOPMENT BANK

6 ADB Avenue, Mandaluyong City

1550 Metro Manila, Philippines

www.adb.org