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Washed Away: The Impacts of Extreme Rainfall on Child Marriage in Bangladesh

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Abstract

Bangladesh has long been exposed to climate-induced disasters, and the literature has paid little attention to their impact on child marriage. This study empirically explores the gendered impact of extreme rainfall on child marriage in Bangladesh and provides a comprehensive yet detailed analysis using high-resolution weather data and nationally representative rural household survey. The duration analysis in this paper shows that women exposed to one standard deviation more extreme rainfall are at an increased risk of child marriage by 5.5%. However, we find no evidence that child marriages driven by extreme rainfall lead to early childbirth in women. We also report that extreme rainfall has no statistically significant impact on men's child marriages. The main finding is consistent across several decades of cohort and robust to migration, which might threaten internal validity. We also highlight that our main findings are driven by households living in non-coastal regions, with significant heterogeneity across divisions.

Keywords: Bangladesh, child marriage, extreme rainfall, survival analysis, weather shock

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1. Introduction

Child marriage – the union of a child under the age of 18 years with another child or adult – is a widespread social issue affecting millions of girls in developing countries. Despite the declining prevalence of child marriage worldwide, the United Nations Children's Fund (UNICEF, 2020) has reported high rates of child marriage in Bangladesh, with a prevalence of 51%.[1] It is also noted that girls are more exposed to such practices than boys. Child marriage is considered to have adverse life-long consequences for women, including poor educational outcomes, poor maternal and child health, and high exposure to violence (Anukriti & Dasgupta, 2018).

Recently, a few studies have explored the causal relationship between weather shocks and child marriages. Corno et al. (2020) show that in the equilibrium, an adverse income shock resulting from increased temperature could discourage (encourage) child marriage when girls' families (boys' families) are obliged to pay dowry (brid price). It is because they consider marriage payment as a source of consumption smoothing mainly for girls' family. They also provide empirical evidence in Sub-Saharan Africa and India to support their theoretical predictions.

Although dowry is prevalent in Bangladesh, the impact of weather shocks on child marriage through marriage payments is a priori ambiguous. Do et al. (2013) provide a theoretical foundation and empirical evidence that kinship marriage serves as an alternative when dowries are burdensome. Mobarak et al. (2013) also show that wealth shocks caused by floods increase within-family marriages in regions without sufficient measures of flood protection as it reduces need for dowry payments.

[1] The prevalence rate of child marriage is measured by a percentage of women aged 20 to 24 years who were married or entered into union before the age of 18 years.

Additionally, it is conjectured that damaged housing and displacement resulting from extreme water shocks will incentivize parents to marry off their daughters at a younger age because of the higher risk of being attacked by sexual predators. Increasing literature on climate-induced disasters reports that social norms restricting interaction between men and women predispose women to hesitate to use public shelters (Cannon, 2002) and are subject to harassment at community centers (Azad et al., 2013). In this regard, this study aims to fill the gap in the literature by providing the first empirical evidence of how extreme water shocks affect child marriage in the context of Bangladesh, a nation with solid and persistent gender norms and high vulnerability to various water shocks.

The literature points out that girls' relatively low economic contribution to their families and social norms that value their virginity are the two major driving forces behind child marriage (Warner, 2004). In traditional society, women are valued more for their potential fertility, while men are valued more for their income prospects (Bergstrom & Schoeni, 1996). Low-income families do not want to invest in their daughters, whose human capital would be transferred to the husband's family upon marriage. Men prefer younger brides from the demand side because of their longer fertility and tendency to conform to the rules of their husbands and families (Jensen & Thornton, 2003). When women's economic opportunities are limited, the marriage market, which values girls' virginity and fertility, motivates families to marry their daughters at a younger age.

A natural disaster, such as a flood, would only aggravate the environment surrounding young women in Bangladesh. Figure 1 presents a geographic map of the country. The country is located in the middle of the two most contrasting topographies in the world: the Bay of Bengal in the south and the Himalayas in the north. It is also located in one of the largest deltas in the world formed by three rivers: Ganges, Brahmaputra, and Meghna. This natural environment causes severe weather shocks in Bangladesh as a result of floods. Approximately 20% of land in Bangladesh experiences annual flooding (Chowdhury, 2000). Extreme floods in 1987-88 and 1998 caused thousands of deaths, damage to agriculture and industry outputs, and wrecked the necessary infrastructure (Mirza, 2002). Moreover, a cyclone in 1991, which killed approximately 138,000 people, manifested the disproportionate nature of the natural disaster toward females. A survey by Ikeda (1995) reports that female mortality rates were estimated to be four or five times larger than that of males.

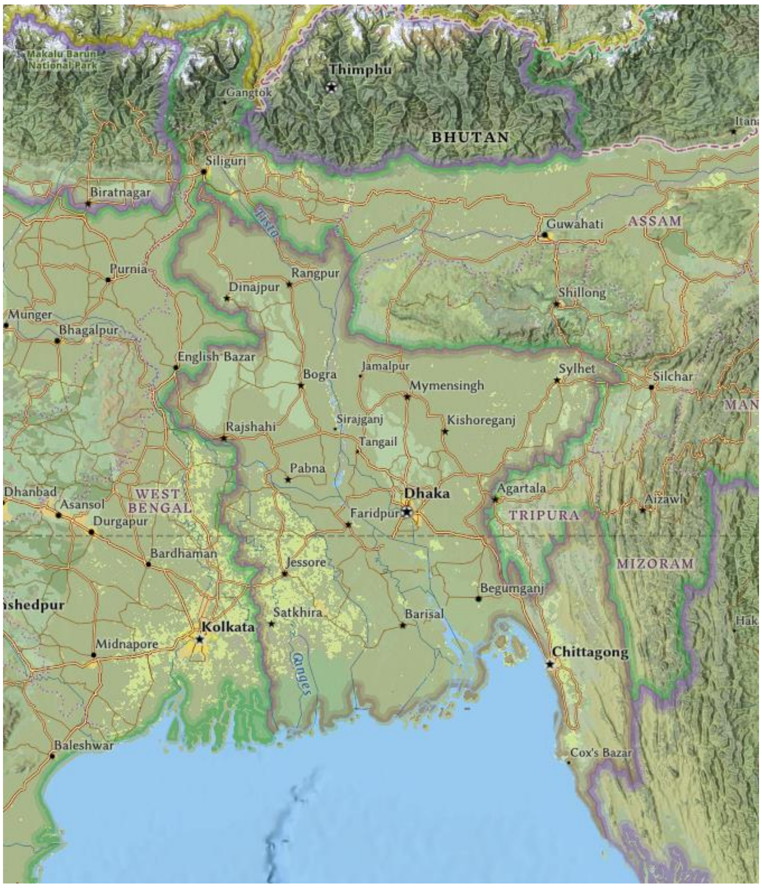

Figure 1. A Map of Bangladesh.

Source: Esri, USGS.

Despite its importance, studies on the impact of natural disasters on child marriage in Bangladesh are scarce. Ahmed et al. (2019) and Asadullah et al. (2021) report valuable insights into child marriages and extreme weather conditions in Bangladesh using data from several selected villages. Tsaneva (2020) shows that droughts encourage child marriage through negative income shocks and marriage payments. Carrico et al. (2020) also highlight that heat waves and dry spells encourage young women's marriage with less desirable spouses. To the best of our knowledge, this is the first study in Bangladesh that empirically examines the impact of water shocks on child marriage using nationally representative data.

In this study, we construct a measure for extreme rainfall shocks, using the long-term precipitation data sourced from APHRODITE (Asian Precipitation-Highly-Resolved Observational Data Integration Towards Evaluation), the most high-resolution weather data available in Asia. Our measure of extreme weather is the share of days each grid-point experienced extreme rainfall above a certain threshold level, which enables us to capture the experience of heavy rainfall in a very local area over a short period of time.

The measures of extreme rainfall shock are then matched to individual panel data constructed from the Bangladesh Integrated Household Survey (BIHS), which surveyed a nationally representative sample of the rural population. The sample of women and men are born between 1960 and 2005, with information regarding year of marriage, year of first birth (women only) along with GPS (Geographic Coordinate System) coordinates of residence. Following the methodology used by Corno et al. (2020), we perform a duration analysis to assess the impact of extreme rainfall shocks on child marriage and early birth.

Then, the study examines whether the main results are robust to potential threats, including marriage migration and model misspecification. We address the migration issue by employing BIHS's special module on child marriage to identify women's exact locations before marriage. We also explore the lagged and contemporaneous effects of extreme rainfall on women's child marriage and examine the heterogeneity of results across several decades of cohorts. The differential impacts of weather shocks on sub-samples are explored across various geographical characteristics of residences and divisions.

2. Data and Empirical Strategy

2.1. APHRODITE and Measures of Extreme Rainfall

We construct a measure of extreme rainfall shock using the daily precipitation data reported at each grid-point. Our measure of weather shock ($W_{g\tau}^{P}$) is defined as the share of days (t) in each grid-point (g) that experienced extreme rainfall over the division-specific (d) P percentile over the total number of days (T) in the year (τ) using Equation (1):

$$W_{g\tau}^{P} = \frac{1}{T}\sum_{t=1}^{\mathrm{T}} 1[rainfall_{gt\tau} \geq P\ percentile^{d}]. \tag{1}$$

$P\ percentile^{d}$ is a division-specific threshold that we employ to define extreme rainfall.[2] We calculate each threshold value from the long-term rainfall data from 1951 to 2015 for each division d at the 75th, 80th, and 90th percentiles. Compared to other conventional measures, such as cumulative rainfall, our measure in Equation (1) is advantageous for capturing unusual and extreme rainfall experienced by local areas. The denominator can be adjusted to crop-specific cultivation period as we examine the impact of water shock on crop production in Appendix Section A.2. Our main results in Table 2 are robust to that alternative weather shock measure.

To construct a measure of weather shock, that is $W_{g\tau}^{P}$, we utilize daily precipitation data sourced from APHRODITE, the most high resolution weather data available in Asia, constructed by the National Center for Atmospheric Research (Yatagai et al., 2012). We combine its two versions[3] and construct long-term daily precipitation data covering the period

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[2] Bangladesh is consisted of 8 following divisions at top-level administrative levels: Barisal, Chittagong, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet.
[3] We utilize APHRODITE V1101EX_R1 (Yatagai et al., 2012) for the early period from 1969 to 1997

from 1969 to 2015. As documented by Auffhammer et al. (2013), interpolation and timing discrepancies in most gridded weather data raise concerns regarding potential measurement error. Such a measurement error can be partially addressed in our setting, as the recent APHRODITE provides precipitation data in each 0.25 × 0.25-degree grid[4] while conserving the original station value at each 0.05 grid box. This high resolution weather data helps capture extreme and localized weather shocks without underestimation. Besides, the data are adjusted for differences in the observation time.

Additionally, we use daily temperature data from APHRODITE[5] to construct a measure for extreme heat using Equation (1). Various weather variables tend to correlate with each other, causing omitted variable bias when not properly controlled (Hsiang et al., 2013). In this study, extreme heat is defined as the share of days each grid-point experienced a temperature above 90 °F (equivalent to 32.2°C) over the year, a conventional threshold employed in the literature (Park et al., 2020).

Figure 2 shows the spatial distribution of extreme rainfall occurrences above the 90th percentile, averaged over the period 1969-2015. This distribution demonstrates the prevalence of excess rainfall across Bangladesh. Extreme rainfall shocks occur more frequently in riverine areas, Sylhet-the northeastern part of Bangladesh, and in coastal regions.

To test the validity of our measures of extreme rainfall, we examine the association between extreme weather shocks and the yield production of major crops in Bangladesh. The estimation results show that our constructed measure of extreme rainfall have a negative and

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and the end-of-the-day adjusted version of APHRODITE V1901 (Yatagai et al., 2012) for the later period from 1998 to 2015.

[4] It is approximately equivalent to 27.75 km × 27.75 km.

[5] We utilize AphroClim_V1808 (Yasutomi et al., 2011) for the period from 1969 to 2015.

significant impact on major crop yield changes from 1969/70 to 2014/2015 in Bangladesh. The details of this exercise are available in Appendix, Section A.

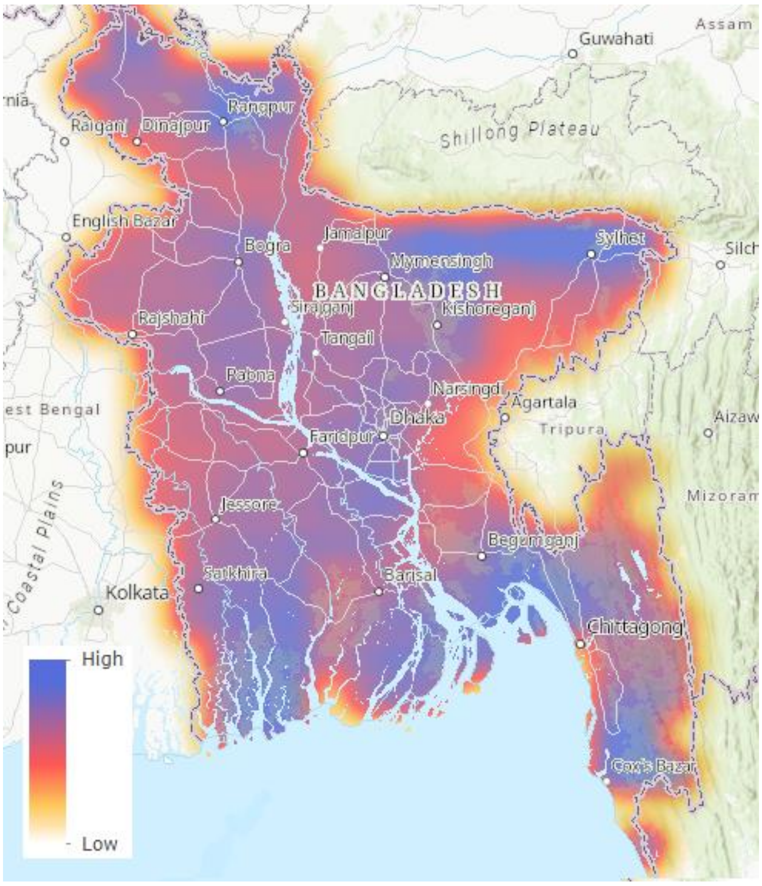


Figure 2. Spatial Distribution of Extreme Rainfall in Bangladesh between 1969-2015.

Note: Due to a lack of daily precipitation data on the neighboring countries, boundary areas in Bangladesh are depicted as yellow.

Source: Esri, USGS.

2.2. BIHS Data

Our study aims to explore how extreme weather shocks affect child marriage over a long period. For our analysis, we employ the latest third round (2018-2019) of the BIHS conducted by the International Food Policy Research Institute (International Food Policy Research, 2020). The BIHS is the only nationally representative survey in rural Bangladesh that contains detailed retrospective data on men's and women's year and age at marriage, year of first childbirth,[6] and GPS geographic coordinates of each village. Such features of the BIHS allow us to accurately estimate the effects of local and extreme weather shocks on child marriages in rural Bangladesh.

The BIHS 2018-2019 has a special module that provides women's residential information before marriage. Although the sample size is limited, this module enables us to assess the robustness of the main results to a potential threat to our identification strategy that might result from migration. The BIHS 2018-2019 covers 5,605 rural households in 325 primary sample units. Among the respondents, 81% are men and 19% are women.[7] To investigate the impacts of extreme rainfall on child marriage over a long period while ensuring a sufficient number of observations in each cohort, we restrict our sample to women and men born between 1960 and 2004.

2.3. Empirical Specification

We estimate a simple discrete approximation of a duration model based on Corno et al. (2020) and Currie and Neidell (2005) to assess the effect of weather shocks on child marriages. To conduct the survival analysis, we first construct person-year panel data from a sample of women and men in the 2018-2019 BIHS. As the GPS coordinates of each household are reported in the BIHS, the person-year panel data are linked to the weather data construct in Section 2.1. As villages are smaller than 0.25 × 0.25-degree grids, multiple small villages are often matched to each grid-point in the weather data.

[6] The respondents are asked to recall the age when they got married. If they married more than once, they are asked to report the age of their first marriage. The age of the women's first childbirth is reported in the same way. If the woman has a child or children, she is asked to report the age of their first childbirth.
[7] Among the household heads who participated the survey, males account for 87.5% and females account for 12.5%.

To examine the impact of weather shocks on the hazard of child marriage, based on Corno et al. (2020), we first estimate the probability of marriage of women i in the grid-point g born in cohort k and getting her first marriage at age a as follows:

$$M_{i,g,k,a} = \delta + \beta W_{g,k,a} + Age_a + \omega_g + D_d + \gamma_k + \varepsilon_{i,g,k,a}, \quad (2)$$

where $M_{i,g,k,a}$, a dependent variable in this analysis, is a binary variable coded as 0 until the year before marriage and 1 in the year the woman marries. In this analysis, the duration of interest is the time between t_0, the age at which a woman is first at risk of getting married, and t_m, the age at which she enters her first marriage. We identify t_0 to be 9 years as that is the minimum age at which women in our sample reported getting married for the first time. Once a woman is married at t_m, she no longer appears in the data. We set t_m to 18 years, the legal marriage age for women in Bangladesh. Women married after the age of 18 re right-censored.[8] Additionally, given that marriage culture and practices in India have influenced Bangladesh, we also consider the age of 15 as t_m. In 2012, the Delhi High Court ruled that a Muslim girl could marry as per her choice at the age of 15 if she had attained puberty, and the ruling was followed by several other high courts in India (The Times of India, 2012).

$W_{g,k,a}$ is a measure of the weather shocks in grid-point g during the year wherein the woman born in year k is of age a. It measures the share of days in each grid-point experiencing extreme rainfall over three different percentiles-75th, 80th, and 90th–over the whole year. Most rice farmers in Bangladesh harvest two or three times a year because of their fertile soil and ample water supply. Therefore, we assume that most rural households are affected by extreme

[8] As stated in Corno et al. (2020), for example, a woman reporting that she gets married at age 12 would appear four times in the regression for child marriage; her marriage regression vector would be $M_{i,c,k,9}$, $M_{i,c,k,10}$, $M_{i,c,k,11}$, $M_{i,c,k,12}$=0, 0, 0, 1. For the woman who is not married by the age of 15 and appear in the data seven times, then her marriage regression vector would be a string of zeros.

weather shocks throughout the year. β is the main coefficient of interest, which captures the effect of extreme rainfall on the probability of child marriage.

Next, we include a set of fixed effects (FE) in all the specifications. We include age FE, Age_a, to account for the different probabilities of marriage at different ages. ω_g and D_d are grid-point and division FEs, respectively, which control for time-invariant local unobservable characteristics, such as geographic, economic, and cultural factors. Year-of-birth FE γ_k are also included to control for cohort effects. We estimate regressions with standard errors clustered at the grid-point to allow for serial correlation in the error terms across females in the same area.

Including grid-point and year-of-birth FE in our specification allows us to identify the impact of extreme rainfall on child marriage from within-grid and within-year-of-birth variations in weather shocks and marriage outcomes. We assume that different measures for extreme rainfall included in $W_{g,k,a}$ are reasonably exogenous to potential confounders, such as household conditions around the time of women's marriage, as also noted by Corno et al. (2020) and Vogl (2013).

To examine whether weather shocks in the year of marriage lead to early childbirth, we estimate the following equation:

$$F_{i,g,f,a} = \delta + \beta_m W_g^m + \beta_f W_g^f + Age_a + \omega_g + D_d + \theta_f + \varepsilon_{i,g,f,a}, \tag{3}$$

where $F_{i,g,f,a}$, indicates whether the woman i aged a living in the grid-point g married in year m and had the first childbirth in year f before the age of 18. W_g^m and W_g^f are measures for the weather shocks, in the grid-point g during the year of marriage m and in the year of first childbirth f. This specification allows us to investigate whether weather shocks in the marriage year induce early fertility when controlling for weather shocks in the childbirth year. Age_a,

ω_g , D_d, and θ_f are the age, grid-point, division, and year of first childbirth FEs, respectively. We estimate the regressions with standard errors clustered at the grid-point in the same manner.

In Table 1, Panel A shows the descriptive statistics for the unique individual – marriages and childbirths, while Panel B shows the statistics for the person-year sample. Panel A of Table 1 supports the prevalence of child marriages in Bangladesh, which is consistent with the literature. The mean age of first marriage for females is around 17 years, which is far lower than that of males (23.7 years). Among married females, 60.6% married before the age of 18 years and 17.5% married before the age of 15 years in our sample. These figures are much higher than those of males. Panel B of Table 1 reports the average annual hazard for child marriage during the duration of analyses. The average annual hazard that women would enter marriage between ages 9 and 17 is 0.073, which is much higher than that of men (0.003).

Table 1. Summary Statistics of the Regressions Sample.

	Women	*N*	Men	*N*
Panel A. Unique individuals				
(Mean) Age of first marriage	17.0	6,448	23.7	4,055
Percent married between ___ among married				
Ages 9 and 17	60.6%		3.6%	
Ages 9 and 14	17.5%		0.2%	
(Mean) Age of first childbirth	19.3	5,914	------	
Percent with first childbirth between ___ among women who gave childbirth				
Ages 12 and 17	29.2%		------	
Panel B. Survival data (Persons-year sample)				
The average annual hazard of child marriage ___				
Between ages 9 and 17	0.073		0.003	
Between ages 9 and 14	0.028		0.0003	

Notes: The main sample contains individuals born between 1960 and 2005. Marriage and childbirth information is available in the BIHS 2018-2019 survey.

3. Impacts of Extreme Weather Shocks on Child Marriage in Bangladesh

The estimation of Equation (2) using various measures of extreme rainfall is reported in Table 2 using a sample of females born between 1960 and 2004 and their marital outcomes until 2015. The effects of extreme rainfall shock on marriage hazards before the age of 18 are reported in Columns (1)–(3), and those before the age of 15 are reported in Columns (4)–(6).

Table 2. Impacts of Extreme Rainfall on Child Marriage for Women.

	Under the age of 18			Under the age of 15		
	(1)	(2)	(3)	(4)	(5)	(6)
The share of days experienced rainfall greater than ___ of the distribution	90th	85th	75th	90th	85th	75th
Extreme rainfall	0.108*	0.108**	0.095**	0.072*	0.077**	0.053*
	(0.055)	(0.046)	(0.040)	(0.041)	(0.033)	(0.031)
Constant	0.027	0.022	0.014	0.012	0.008	0.006
	(0.020)	(0.021)	(0.023)	(0.020)	(0.021)	(0.022)
Age at *t(0)*			9			
Mean of Y	0.073	0.073	0.073	0.029	0.029	0.029
Coefficient × std. dev	0.004	0.004	0.005	0.003	0.004	0.003
Observations	50,548	50,548	50,548	37,764	37,764	37,764
R-squared	0.121	0.121	0.121	0.063	0.063	0.063
Birth Year FE	✓	✓	✓	✓	✓	✓
Age FE	✓	✓	✓	✓	✓	✓
Grid FE	✓	✓	✓	✓	✓	✓
Division FE	✓	✓	✓	✓	✓	✓

Notes: The sample contains females born between 1960 and 2004. The measures of extreme rainfall are defined as the share of days each grid-point experienced extreme rainfall greater than the threshold over a year. The 90th, 85th, and 75th percentiles of the rainfall distribution are employed as the thresholds for extreme rainfall. Errors are clustered within each grid-point in all regressions to address the correlation among the error terms. Each grid-point size is 0.25 × 0.25-degree. All regressions are weighted by the population weights. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Columns (1)–(3) in Table 2 show that the coefficients for extreme rainfall are statistically significant across all three measures of extreme rainfall, which are measured as the share of days that each grid-point experienced rainfall greater than the 90th, 85th, and 75th percentiles of the distribution, respectively. To better understand the estimated coefficients, in Table 2, we provide a coefficient multiplied by one standard deviation of the weather variable employed in each regression. Specifically, Column (1) presents that young females who were exposed to one standard deviation more of extreme rainfall between the ages of 9 and 18 are 0.4 percentage points (pp) more likely to get married in the same year. Considering that the average annual marriage hazard for women under the age of 18 is 0.073, the effect of a one standard deviation increase in the experience of extreme rainfall corresponds to an approximately 5.5% increase in the child marriage hazard. The magnitude and statistical significance of the estimated effects are consistent across the different measures of extreme rainfall in Columns (2) and (3).

Columns (4)–(6) in Table 2 report the estimation results, where we estimate the effects of extreme rainfall shocks on the probability of child marriage under the age of 15. Column (5) shows that females who were exposed to one standard deviation more of excessive rainfall between the ages of 9 and 15 are 0.3 percentage points (pp) more likely to get married in the same year. The average annual marriage hazard for this age group is 0.029, implying that the effect of a one standard deviation increase in the experience of extreme rainfall corresponds to a 10.3% increase in child marriage hazard.

Table 3 reports estimation results examining the impacts of extreme rainfall on the early marriage of young men. In Columns (1)-(3), we find no evidence that extreme heavy rainfalls, regardless of their levels, have an effect on early marriage among young men in Bangladesh.

Table 4 presents the estimation results of Equation (3), which aims to examine the impacts of extreme rainfall on the early fertility of women. The sample of females is the same as the females in Table 2. The estimations results demonstrate statistically insignificant coefficients of extreme rainfall at the year of marriage or first childbirth on women's early childbirth under the age of 18 regardless of the levels of the heavy rainfall. As Warner (2004)[9] argued, if child marriage is more associated with having women as free labor in Bangladesh,

[9] Warner (2004) described child marriage as a form of forced labor as it is very likely that girls who are subject to child marriage lack a sense of independence and means to argue against her fate, and they are highly likely to provide "unremitting services" to their husband and husband's family.

early marriage does not necessarily result in early fertility.

Table 3. Impacts of Extreme Rainfall on Child Marriage for Men.

	Marriage under the age of 18		
	(1)	(2)	(3)
The share of days experienced rainfall greater than ___ of the distribution	90th	85th	75th
Extreme rainfall	0.024	0.017	0.015
	(0.016)	(0.012)	(0.010)
Constant	-0.003	-0.003	-0.004
	(0.006)	(0.006)	(0.007)
Age at *t(0)*		9	
Mean of Y	0.0034	0.0034	0.0034
Coefficient × std. dev	0.0008	0.0007	0.0007
Observations	36,327	36,327	36,327
R-squared	0.024	0.024	0.024
Birth Year FE	✓	✓	✓
Age FE	✓	✓	✓
Grid FE	✓	✓	✓
Division FE	✓	✓	✓

Notes: The sample includes males born between 1960 and 2005. Refer to the notes in Table 2 for the definitions of the variables and further information. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 4. Impacts of Extreme Rainfall on Women's Early Childbirth.

	Childbirth under the age of 18		
	(1)	(2)	(3)
The share of days experienced rainfall greater than ___ of the distribution	90th	85th	75th
Extreme rainfall at the year of marriage	-0.293	-0.381	-0.179
	(0.306)	(0.281)	(0.245)
Extreme rainfall at the year of childbirth	0.294	0.144	-0.009
	(0.232)	(0.207)	(0.169)
Constant	0.906***	0.917***	0.882***
	(0.086)	(0.097)	(0.120)
Age at *t(0)*		9	
Mean of Y	0.0034	0.0034	0.0034
Coefficient × std. dev	0.0008	0.0007	0.0007
Observations	5,465	5,465	5,465
R-squared	0.232	0.232	0.231
Birth Year FE	✓	✓	✓
Age FE	✓	✓	✓
Grid FE	✓	✓	✓
Division FE	✓	✓	✓

Notes: The sample contains females born between 1960 and 2004. Refer to the notes in Table 2 for the definitions of the variables and further information. ***, **, and * indicate statistical significance at

1%, 5%, and 10%, respectively.

4. Robustness Tests

4.1 Robustness to Migration

In this section, we perform a wide array of checks and additional tests on our data to examine the robustness of the main results. As noted by Corno et al. (2020), our main results are exposed to several potential internal validity threats caused by migration. Despite the custom of virilocality in Bangladesh, most women marry someone in the same village (Agarwal, 1994), and some housewives in the household could be from distant villages with different levels of weather shocks. If a female migrated at the time of marriage due to a severe weather shock in her village, her movement would cause an underestimation of our main results in Table 2.

Second, as pointed out by Corno et al. (2020), there is a possibility that a woman and her family might simply migrate after marriage before the survey took place due to a weather shock. The measurement error in weather shocks would cause an underestimation of the effects that the weather shock could have on child marriage. In addition to the issue of migration, most of the primary respondents in the BIHS are males, which might introduce errors in the accuracy of the data given its retrospective nature.

The special module on child marriage in the BIHS 2018-2019 provides a way to identify women's exact location before marriage. The questions in the special module asked all females who are married and surveyed as members of the household during the BIHS's 1st round in 2011. The special module has a smaller sample size and contains a sample of young women aged under 31 years (born after 1981) at the time of the survey. Nevertheless, it provides a useful way to check the robustness of the main findings on marriage migration, when weather shocks are matched according to women's residential locations before marriage as reported in the BIHS 2011 round. Another advantage of using this module is that females are the primary respondents, which might help reduce errors in the original sample, where most of the primary respondents are males. Given that the females in the special module are younger than those in our original sample for early marriage, we are able to explore the recent trends between weather shocks and the timing of marriage before the age of 18 as well as before the age of 15.

Table 5. Impacts of Extreme Rainfall on Early Marriage of Women, Born between 1971 and 2004, using the BIHS's Special Module.

	Under the age of 18			Under the age of 15		
	(1)	(2)	(3)	(4)	(5)	(6)
The share of days experienced rainfall greater than ___ of the distribution	90th	85th	75th	90th	85th	75th
Extreme rainfall	0.276***	0.257***	0.208***	0.135**	0.100*	0.067
	(0.084)	(0.073)	(0.060)	(0.056)	(0.052)	(0.042)
Constant	0.056***	0.042**	0.033*	-0.031**	-0.033**	-0.032**
	(0.015)	(0.017)	(0.019)	(0.013)	(0.015)	(0.016)
Age at t(0)				9		
Mean of Y	0.060	0.060	0.060	0.015	0.015	0.015
Coefficient × std. dev	0.009	0.010	0.010	0.006	0.005	0.003
Observations	18,112	18,112	18,112	13,402	13,402	13,402
R-squared	0.139	0.139	0.139	0.057	0.057	0.057
Birth Year FE	✓	✓	✓	✓	✓	✓
Age FE	✓	✓	✓	✓	✓	✓
Grid FE	✓	✓	✓	✓	✓	✓
Division FE	✓	✓	✓	✓	✓	✓

Notes: The sample includes individuals born between 1971 and 2004. Refer to the notes in Table 2 for the definitions of the variables and further information. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 5 presents the estimation results of Equation (2) using the sample of the special module and child marriage, that is the probability of early marriage of young women before the ages of 15 and 18, as an outcome variable, respectively. Estimates are quite consistent with our main results in Table 2, presenting a larger magnitude of estimated impacts of weather shocks on child marriage. To be specific, Column (2) presents that the young females who experienced extreme rainfall, measured as the share of days in the grid experienced rainfall greater than the 85th percentile of the distribution, between ages 9 and 18 are 2.6 pp more likely to get married in the same year. The average annual marriage hazard for this age group is equal to 0.060. Thus, the effect of one standard deviation increase in the extreme rainfall (0.010) corresponds to a 16.7% increase, which is approximately three times larger than the estimates (5.5%) in Column (2) of Table 2. The larger and statistically stronger estimates in Table 5 support the possibility that the main results in Table 2 could be the lower bound for the impacts of the weather shock on child marriage.

4.2 Robustness to Various Functional Form Specifications

In this subsection, we test the robustness of our main results in Tables 2 and 3 of Section 3 using various functional form specifications. In Table 6, we present the estimation of Equation (2) with additional terms in the specification: one-year lagged variable and two-year lagged variable for extreme weather shocks measured at three different levels. Columns (1)–(3) show that the contemporaneous effects of extreme rainfall on the early marriage of young women under the age of 18 remain statistically strong, with similar magnitudes when compared to Columns (1)–(3) in Table 2. At the same time, the coefficients of past extreme rainfall, which are the coefficients for the one-year lagged term and the two-year lagged term, respectively, are mostly statistically insignificant. This notion suggests that extreme rainfall affects child marriage within a year.

Columns (4)–(6) demonstrate that child marriage under the age of 15 can be better explained by both the contemporaneous and lagged impacts of extreme rainfall. The coefficients of the contemporaneous terms turn out to be slightly larger and statistically stronger than those presented in Columns (4)–(6) in Table 2. Furthermore, the coefficients for one-year and two-year lagged terms exhibit significant and sizable effects across different levels of extreme rainfall. We also conduct post-estimation tests to examine whether there are cumulative effects of extreme rainfall on the probability of child marriage. The results in Table 6 show that cumulative effects are more important in the case of child marriage under the age of 15 and when excess rainfall is measured as the share of days experienced rainfall above the 75th percentile of the distribution, as in Columns (3) and (6).

Table 6. Contemporaneous and Lagged Impacts of Extreme Rainfall on Child Marriage for Women.

	Under the age of 18			Under the age of 15		
	(1)	(2)	(3)	(4)	(5)	(6)
The share of days experienced rainfall greater than __ percentile of the distribution	90th	85th	75th	90th	85th	75th
Contemporaneous term	0.113**	0.110**	0.098**	0.083**	0.089***	0.069**
	(0.055)	(0.046)	(0.040)	(0.041)	(0.034)	(0.032)
1-year lagged term	0.057	0.043	0.055	0.134***	0.128***	0.139***
	(0.055)	(0.046)	(0.041)	(0.042)	(0.038)	(0.033)
2-year lagged term	-0.012	0.026	0.071*	0.054	0.075**	0.103***
	(0.053)	(0.045)	(0.038)	(0.041)	(0.033)	(0.027)
Constant	0.023	0.012	-0.017	-0.005	-0.022	-0.055**
	(0.022)	(0.024)	(0.029)	(0.022)	(0.023)	(0.027)
Test H_0: contemporaneous + lagged terms=0	0.158	0.179*	0.224***	0.270***	0.293***	0.311***
	(1.50)	(1.89)	(2.77)	(3.47)	(4.21)	(4.92)
Age at *t(0)*				9		
Observations	50,548	50,548	50,548	37,764	37,764	37,764
R-squared	0.121	0.121	0.122	0.063	0.063	0.064
Birth Year FE	✓	✓	✓	✓	✓	✓
Age FE	✓	✓	✓	✓	✓	✓
Grid FE	✓	✓	✓	✓	✓	✓
Division FE	✓	✓	✓	✓	✓	✓

Notes: The sample contains females born between 1960 and 2004. Refer to the notes in Table 2 for the definitions of the variables and further information. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

We perform additional robustness checks using 1) an alternative functional form of age in the duration model, 2) an alternative level of clusters, and 3) robustness when extreme heat is controlled[10] in Equation (2). Appendix Tables B1 and B2 report the results. The dependent

[10] When estimating Equation (3), both extreme heats measured in the year of marriage and year of first childbirth are controlled.

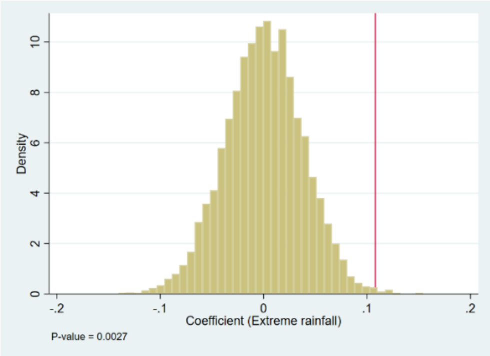
variable employed in Appendix Table B1 is child marriage under the age of 18, whereas early fertility under the age of 18 is examined in Appendix Table B2. Overall, the main findings presented in Tables 2 and 3 are robust and remain consistent across various specifications when the rainfall shock is defined as the share of days wherein each grid experienced rainfall greater than the 85th percentile of the distribution.

4.3 Falsification Test

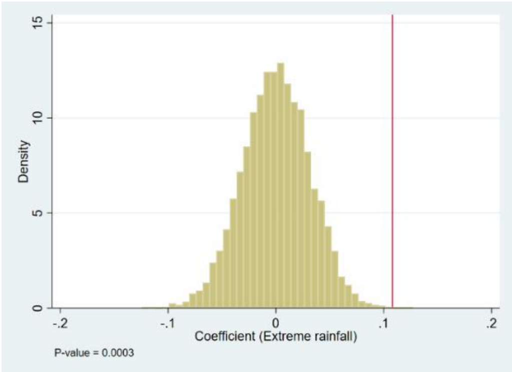
In this subsection, we examine whether the main findings in Table 2 are spurious or biased based on an incorrect model specification. Following Hsiang and Jina (2014) and Miller et al. (2021), we attempt a falsification test by constructing false data where weather shocks are randomized across panel structures (i.e., grid-point and year) holding a dependent variable. Then, Equation (2) is re-estimated using the false data and compared to the main findings in Table 2. The estimates from the false data should yield null results, where the impacts of weather shocks on the early marriage of young women are zero. An additional benefit of this randomization is that we can retrieve the distribution of the null results by repeating the randomization.

Figure 3 shows the null distribution of the estimated β of Equation (2), which captures the effect of extreme rainfall on the timing of child marriage. Weather shocks are randomized across panel structures, that is, division and year, 10,000 times without replacement for each level of extreme rainfall. The red vertical lines indicate the main estimates presented in Columns (1)–(3) of Table 2 for the three different levels of extreme rainfall. For easier comparison, the p-values of the main estimates from Table 2 are calculated using a randomized distribution from the false data. The p-values reported along with the distribution are extremely small, implying that the main findings reported in Table 2 are not spurious relationships between extreme rainfall and women's early marriage.

A. Extreme rainfall greater than the 90th percentile of the distribution



B. Extreme rainfall greater than the 85th percentile of the distribution



C. Extreme rainfall greater than the 75th percentile of the distribution

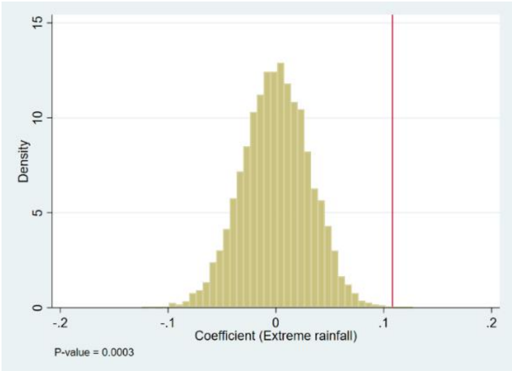


Figure 3. Falsification Test: Impacts of Extreme Rainfall on Early Marriage of Young Women under the Age of 18.

Notes: The null distributions of the coefficients for extreme weather shocks on the probability of child marriage are presented. Refer to Table 2 for definitions of weather shocks. weather shocks are randomized across panel structures, that is, division and year, 10,000 times without replacement for each level of extreme rainfall. The red vertical lines indicate the main estimates presented in Columns (1)–(3) of Table 2 for the three different levels of extreme rainfall. P values are reported at the bottom of each figure.

5. Heterogeneous Effects

5.1. The Impacts of Weather Shock on Child Marriage across Marriage Cohorts

Bangladesh is a fast-growing developing country that has experienced sharp changes in its economy and society. As reported by Hahn et al. (2018) and Shamsuddin (2015), a conditional cash transfer program implemented to increase girls' secondary education not only increased women's attained education and employment but also delayed marriage and fertility. Recent growth in the garment sector also induced girls' school enrollment while delaying marriage and childbirth.

Bangladesh has also implemented several flood control measures with the support of international organizations since the flood disasters of 1987 (Boyce, 1990). Although flood measures require further improvement (Brammer, 2010), Mobarak et al. (2013) also reported that embankments in the late 1980s and the early 1990s reduced within-family marriages due to reduced wealth shocks.

Although it is certainly not the scope of this paper to examine the extent to which all the above-mentioned social and economic changes influence our main findings, we intend to assess whether the main findings reported in Table 2 are driven by certain cohorts using our long-term data of weather shocks and women's marriage. We modified Equation (2) to estimate the impacts of extreme rainfall shocks on the early marriage of women across marriage cohorts, as follows:

$$M_{i,g,k,a} = \delta + \sum_{t=1970s}^{2010s} \beta_t W_{g,k,a} D_t + Age_a + \omega_g + D_d + \gamma_k + \varepsilon_{i,g,k,a}, \quad (4)$$

where the effects of rainfall shock on child marriage $M_{i,g,k,a}$ are estimated across D_t, which is defined as a binary variable indicating the decade when a young woman i got married. The definitions of all other variables are identical to those explained in Equation (2).

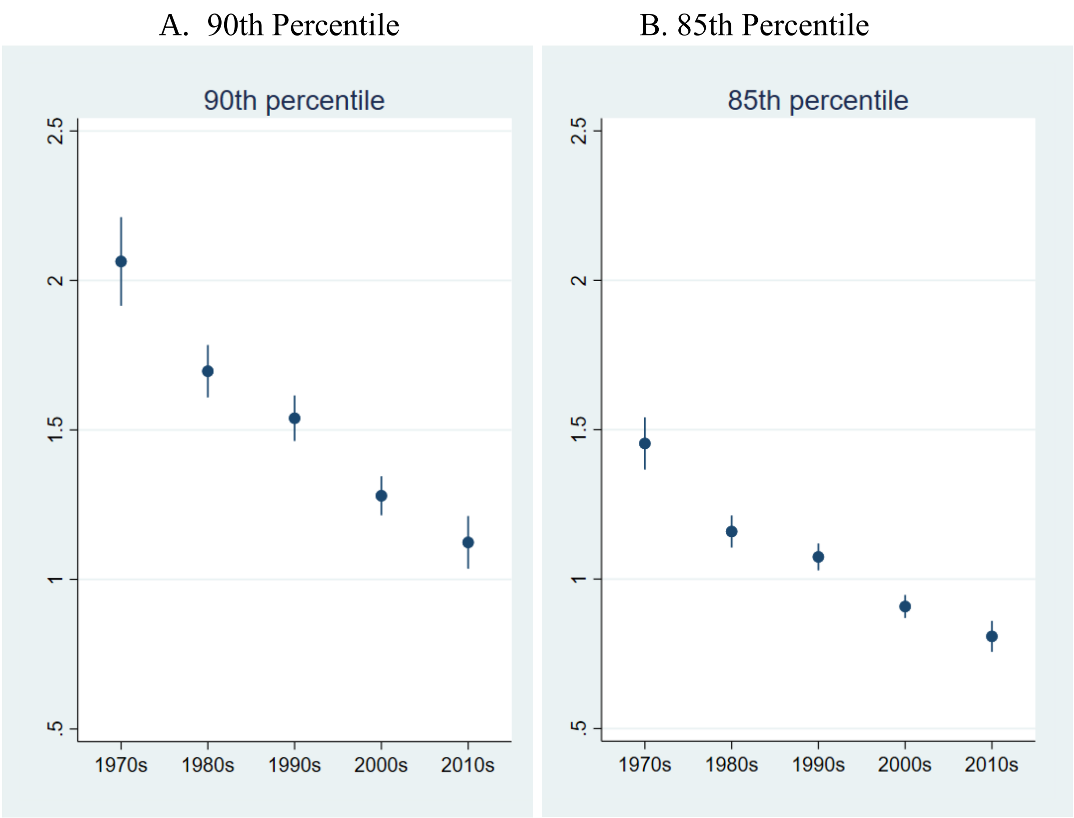


Figure 4. Impacts of Extreme Weather on Early Marriage of Young Women under the Age of 18 by Marriage Cohorts.

Notes: The dots indicate the estimated coefficients for extreme weather shocks by two different levels: 90th percentile and 85th percentile. Refer to Table 2 for definitions of weather shocks. The estimated coefficients are listed in Table B3 of the Appendix. Vertical intervals indicate 95% confidence intervals. Decades of year of marriage D_t are illustrated on the horizontal axis, and the pairwise F-test of the coefficients in Appendix Table B3 is also available in Appendix Table B4.

Appendix Table B3 presents the estimation results.[11] Figure 4 presents the estimated coefficients β_t in Equation (4), where weather shocks are measured as extreme rainfall above

[11] Appendix Table B4 reports a set of pairwise F-tests of the coefficients for the weather shocks that also provide supporting evidence for a decreasing magnitude of the estimates over the marriage year cohorts.

two thresholds (i.e., the 90th percentile and 85th percentile of the distribution). The dots and vertical intervals indicate the estimated coefficients and 95% confidence intervals, respectively. Decades of year of marriage D_t are illustrated on the horizontal axis. Both Figures 4.A and 4.B clearly demonstrate a declining trend across the marriage cohorts but provide consistently significant evidence for the positive effects of extreme weather shock on child marriage. This outcome is consistent with Tsaneva (2020)'s findings that the effect of weather shock, that is, droughts, is largely concentrated among women born in the earlier birth cohorts in the 1950s and the 1960s, and that the effects for later birth cohorts in the 1970s and the 1980s decrease in size and are not statistically significant in Bangladesh.

5.2. Elevation, Distance to Coastline, and Division

In general, the elevation level of Bangladesh is quite low, except for the northern areas close to the Himalayas and Chittagong hills in southeastern Bangladesh. Floods in Bangladesh are most prone to occur around three rivers: the Ganges, Brahmaputra, and Meghna, as well as in coastal reclaimed areas in the southwest (Sciance & Nooner, 2018). However, it would be worthwhile to pay attention to low-elevation areas, as these areas are at risk from sea-level rise and storms, which could aggravate the effects of flooding (McGranahan et al., 2007).

First, we calculate the level of elevation based on each household's geographical information provided by the BIHS data. Following the convention in the literature, we define the low-elevation zone to be less than 10 m above sea level. We then re-estimate Equation (2) using two different samples: households residing in low-elevation areas and those located in high-elevation areas.

Columns (1) and (2) of Table 7 demonstrate that the estimation results showing the positive impacts of weather shock on the early marriage of young women are statistically significant and consistent across specifications for households located in higher areas, while Ganges and Brahmaputra flooded the northwestern part of Bangladesh.

We also measure the distance to the coastline based on households' geographical information and the coastline provided by the National Aeronautics and Space Administration (NASA). We define households living in areas within 30 km of the coastline as coastal area residents. We then divide the sample into two groups, coastal and non-coastal residents, and re-estimate Equation (2). The estimation results are reported in Columns (3) and (4) in Table 7, and they confirm our previous findings that the effect of rainfall shock on child marriage is driven by households living in non-coastal areas.

Columns (5)–(11) in Table 7 present a subsample estimation of Equation (2) using households living in each division of Bangladesh. The estimates show that the effect of rainfall shock on child marriage is most salient in Rajshahi, a district adjacent to the Ganges and Brahmaputra Rivers. The coefficient of extreme rainfall greater than the 90th percentile is also statistically significant in Sylhet, where rainfall combined with flash floods from upstream often causes devastating flooding (Ministry of Planning and Asian Development Bank, 2021). Meanwhile, Chittagong, located in coastal and hilly areas, does not show any supporting evidence consistent with our main findings in Section 3, despite frequent and heavy rainfall in the area. It implies that heterogeneity in the effects of extreme water shocks on child marriage is likely due to differences in flood countermeasures and overall resilience to natural disasters across regions.

Table 7. Heterogeneity in the Effects of Weather Shocks by Elevation, Distance to Coastline, and Division.

Dependent variable:	Women's child marriage under the age of 18										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Elevation		Distance to coastline		Barisal	Chittagong	Dhaka	Khulna	Rajshahi	Rangpur	Sylhet
	Low (<10m)	High (≥ 10m)	≤ 30km	> 30km							
The share of days that experienced rainfall greater than ___ of the distribution											
90th percentile	0.081	0.123*	0.052	0.117*	0.233	-0.102	0.065	0.144	0.556***	0.103	0.127**
	(0.081)	(0.073)	(0.139)	(0.061)	(0.206)	(0.137)	(0.081)	(0.238)	(0.192)	(0.183)	(0.058)
85th percentile	0.088	0.120*	0.019	0.124**	0.031	-0.039	0.114	0.091	0.470***	0.184	0.057
	(0.063)	(0.061)	(0.103)	(0.050)	(0.198)	(0.094)	(0.070)	(0.171)	(0.158)	(0.179)	(0.048)
75th percentile	0.040	0.123**	-0.013	0.117***	-0.017	-0.044	0.131*	0.046	0.410***	0.130	-0.034
	(0.052)	(0.053)	(0.081)	(0.044)	(0.154)	(0.073)	(0.068)	(0.110)	(0.125)	(0.119)	(0.050)
Observations	20,242	29,996	8,292	42,256	3,809	9,528	14,999	4,824	5,383	4,584	7,421

Notes: The sample contains females born between 1960 and 2004. Refer to the notes in Table 2 for the definitions of the variables and further information. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

6. Conclusion

Child marriage is a result of gender inequality but is also a key mechanism supporting and reproducing gender inequality by hampering women’s education, employment, and empowerment. Despite efforts to cut off the vicious cycle and improve women’s education and empowerment, Bangladesh has the highest prevalence of child marriages in South Asia (UNICEF, 2020). The literature also reports an increasing trend of extreme rainfall in Bangladesh along with global warming (Mirza et al., 2001; Shahid, 2011).

This study provided powerful evidence of a strong causal relationship between extreme rainfall and women’s early marriage in rural Bangladesh. Benefitting from high-resolution daily precipitation data, we were able to capture extreme and localized weather shocks without underestimation. Not only did our study provide robust evidence of the encouraging effects of extreme rainfall on women’s child marriage, but it also showed that there are no such effects of extreme rainfall on men’s early marriage or women’s early childbirth.

The findings reported in this study can serve as a wake-up call. Although this study is limited in identifying proper policy instruments and mechanisms through which extreme rainfall encourages child marriage, its findings can be utilized to support practices suggested in the previous literature to mitigate the impact of weather shock on women’s child marriage. Policies to support women’s safety and income during the weather shocks such as ensuring women’s safety in shelters, and providing women with economic opportunities, could be considered in the context of child marriage.More research is required to understand to what extent women’s child marriage induced by weather shocks would hinder their human capital development and worsen gender inequality in the context of developing countries.

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Online Appendix for "Washed Away: The Impacts of Extreme Rainfall on Child Marriage in Bangladesh"

A. Impacts of Extreme Weather Shocks on Crop Yield Change in Bangladesh

A.1. Rice Cultivation in Bangladesh

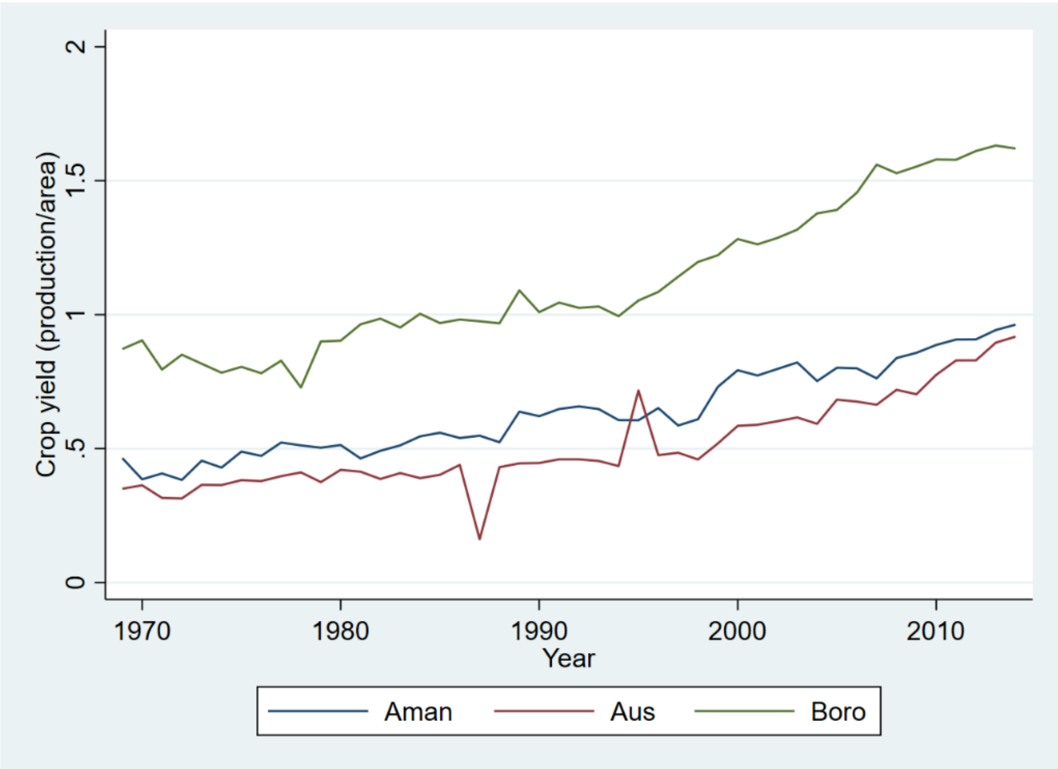
Bangladesh experiences a monsoon between mid-June and September when most rainfall occurs. There is very little precipitation from November to March, whereas pre-monsoon showers can be seen between April and May. It is hot during the monsoon and pre-monsoon seasons, with daily highs above 30°C and low temperatures of around 25°C. The dry season between November and March is characterized by pleasant warm days with an average temperature between 20°C and 25°C.

Bangladesh is an agrarian country where rice is the dominant crop. The major crops are Aus rice, Aman rice, Boro rice, jute, potatoes, and wheat. Aman, Aus, and Boro rice differ in their planting and cultivation periods (Sarker et al., 2012; Shelley et al., 2016). Broadcast seeding is the standard practice for Aus rice, whereas transplantation is the standard practice for Boro rice. Aman rice is planted in both ways. Aman rice, the most cultivated rice in Bangladesh, is planted in April, transplanted in July, and harvested in December. Aus rice is planted in March, cultivated during the pre-monsoon period, and harvested in August. Boro rice is dry-season rice that is transplanted during the early dry season and is harvested in to June.

Owing to differences in cultivation period and planting, each crop is exposed to different climate shocks (Shelley et al., 2016). Aman rice is vulnerable to drought and floods during transplantation or harvest periods. Although direct seeding often makes crops more susceptible to water stress, Aus rice has a strong tolerance to potential drought during its planting and reproduction stages. However, floods during the harvest period can lead to serious crop losses. Similarly, Boro rice harvested and produced on the river bottom can be severely damaged by flash floods during the pre-monsoon period.

A.2. Crop Yield Data and Estimation Results

In this subsection, we explore the association between extreme weather shocks and yield production of three major crops in Bangladesh to validate our measure of extreme weather. In Bangladesh, crop production is highly vulnerable to extreme weather shocks such as floods and droughts (Ministry of Planning and Asian Development Bank, 2021).



Appendix Figure A1. Trends of Crop Yields in Bangladesh, 1969/1970 -2014/2015.

Notes: Authors' calculation using "45 years of Agriculture Statistics for Major Crops" published by the Bangladesh Bureau of Statistics (2018).

For the analysis, we use crop yield statistics for major crops published by the Bangladesh Bureau of Statistics (Bangladesh Bureau of Statistics, 2018). It provides data on annual production, size of production area, and yield rate for major crops in Bangladesh from 1969/70 to 2014/2015. We employ yield data for three major crops, Aman rice, Aus rice, and Boro rice, as their production areas account for 47%, 16%, and 24% of the total crop production in Bangladesh, respectively. Each crop differs in planting and cultivation period[1] (Sarker et al., 2012; Shelley et al., 2016). Appendix Figure A1 shows the long-term trends for each crop yield.

We aggregate crop yield data within seven divisions in Bangladesh: Barisal, Chittagong, Dhaka, Khulna, Mymensingh, Rajshahi, and Sylhet.[2] Following Li et al. (2019), we calculate yield changes as the percentage difference between the yield and its predicted yield[3] in each division. We utilize a simple linear trend model to calculate the predicted yield to capture the improvement in crops, cultivation, and irrigation systems over time.

We use the following equation to explore the relationship between extreme weather and crop production in Bangladesh:

$$Yield\ change_{d\tau} = \alpha + \beta W_{d\tau} + D_d + \varepsilon_{d\tau}, \qquad \text{(A1)}$$

where $W_{d\tau}$ is a measure of weather shocks in division d and year τ. The weather shock measures in Section 2.1 are reconstructed for this particular analysis. Given that crop yield data is only available at the division level and there are multiple grid-points in each division, the measure of weather shock ($W_{d\tau}$) is redefined as the share of grid-point-days experiencing extreme rainfall in each division over the crop's cultivation period from planting to harvest

[1] Aman rice is cultivated from April to December; Aus rice from March to August; and Boro rice from November to June.

[2] We exclude the Rangpur division as it is the northern division bordered by India and the farthest from the delta region with a relatively high altitude often affected by flash floods as well as regular floods.

[3] We use the following equation to obtain the predicted yield in each division d and τ : $Yield\ change_{d\tau} = (Yield_{d\tau} - Yield\ trend_{d\tau})/Yield\ trend_{d\tau} \times 100$

every year. The 75th, 85th, and 90th percentiles of the rainfall distribution are employed as the threshold for extreme rainfall, while 90 °F is employed as a threshold for extreme heat. D_d is a division fixed effect (FE) that controls for geographic characteristics.

Appendix Table A1 shows the summary statistics of the yield changes and weather shocks for the Aman and Aus rice. The means of the weather shocks show that extreme rainfall is more prevalent than extreme heat in Bangladesh during the sample period. Both Aman and Aus rice show sizable standard deviations in their yield changes, suggesting significant volatility in crop production.[4]

Appendix Table A2 presents the estimates of Equation (A1) using three measures of extreme rainfall for Aman, Aus, and Boro rice. Columns (1)–(3) report the estimation results for Aman rice. Column (1) shows that extreme rainfall, defined as the share of each grid-point-days experiencing rainfall greater than the 90th percentile, has a negative impact on the yield change of Aman rice. On average, 0.1 grid-point-days of the divisions experience extreme rainfall shock implying a 9.7% (=-97.15×0.1) point decline in the yield change of Aman rice. The impacts of excess rainfall on the yield change remain significant with a similar magnitude when we try different measures, as shown in Columns (2) and (3). Extreme heat also adversely affectes the yield change of Aman rice. The sizable and statistically significant impacts of excess rainfall are also observed in the case of Aus rice as well. Columns (4)–(6) highlight that heavy rainfall has negative impacts on Aus rice production, while extreme heat shows no such impact. As demonstrated in Columns (7)–(9), the effects of extreme rainfall shocks on the production of Boro rice show results similar to those for Aman and Aus rice, even though Boro rice is mostly cultivated during the dry season.

[4] This is also similar with the case of Boro rice. The summary statistics for the Boro rice can be available upon request.

Appendix Table A1. Summary Statistics of Crop Yields and Extreme Weather during Cultivation Period, 1969/70-2014/2015.

Aman rice (N=322)	Mean	Standard deviation	Min	Max
Aman Rice's Yield Change	0.227	10.57	-41.85	40.27
The share of grid-days experienced rainfall greater than ___ of the distribution				
90th percentile	0.101	0.0249	0.0296	0.168
85th percentile	0.151	0.0315	0.0597	0.233
75th percentile	0.251	0.0396	0.139	0.360
The share of grid-days over 90°F	0.00845	0.0150	0	0.0879

Aus rice (N=322)	Mean	Standard deviation	Min	Max
Aus Rice's Yield Change	0.840	18.19	-76.11	69.42
The share of grid-days experienced rainfall greater than ___ of the distribution				
90th percentile	0.100	0.0282	0.0264	0.195
85th percentile	0.151	0.0359	0.0486	0.263
75th percentile	0.251	0.0472	0.118	0.392
The share of grid-days over 90°F	0.0124	0.0224	0	0.131

Notes: Yield change is defined as the percentage difference between the yield and its predicted yield obtained from a simple linear trend model for each division. The measures of extreme rainfall are defined as the share of grid-point-days experienced extreme rainfall in each division during each crop's cultivation period. The 90th, 85th, and 75th percentiles of the rainfall distribution are employed as the thresholds for extreme rainfall. Extreme heat is defined as the share of grid-point-days experienced a temperature above 90 °F (equivalent to 32.2°C) during each crop's cultivation period.

Appendix Table A2. Extreme Weather and Changes in Crop Yield for Aman, Aus, and Boro rice.

	Crop yield change (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Aman rice			Aus rice			Boro rice	
The share of grid-days experienced rainfall greater than ___ of the distribution	90th	85th	75th	90th	85th	75th	90th	85th	75th
Extreme rainfall	-97.15***	-67.66***	-45.64***	-158.3***	-116.7***	-75.38***	-156.4***	-115.7***	-70.95***
	(21.67)	(17.14)	(13.21)	(34.04)	(24.90)	(18.22)	(31.78)	(26.13)	(18.86)
Extreme heat	-118.6***	-122.6***	-125.8***	17.77	7.084	3.984	-201.1***	-213.0***	-192.8***
	(41.54)	(41.82)	(42.50)	(58.92)	(60.83)	(62.56)	(44.08)	(47.17)	(45.40)
Division FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Constant	11.03***	11.49***	12.75***	16.52***	18.34***	19.71***	18.09***	19.82***	19.89***
	(2.347)	(2.737)	(3.442)	(3.742)	(4.147)	(5.021)	(3.791)	(4.528)	(5.205)
Observations	322	322	322	322	322	322	322	322	322
R-squared	0.058	0.046	0.034	0.064	0.055	0.040	0.104	0.087	0.051

Notes: Yield change is defined as the percentage difference between the yield and its predicted yield obtained from a simple linear trend model for each division. Division FE and robust standard errors are employed in all the regressions. Refer to the notes in Appendix Table A1 for the definition of the weather shock measures. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Appendix Table A3. Contemporaneous and Lagged Impacts of Extreme Weather and Crop Yield Change for Aman and Aus Rice.

	Crop yield change (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
		Aman rice			Aus rice	
The share of grid-days experienced rainfall greater than __percentile of the distribution	90th	85th	75th	90th	85th	75th
Contemporaneous term	-87.49***	-60.28***	-40.47***	-160.1***	-112.8***	-70.71***
	(22.39)	(17.94)	(13.86)	(35.76)	(25.78)	(18.24)
One-year lagged term	8.248	6.274	0.821	-90.10***	-72.18***	-52.22***
	(21.21)	(16.93)	(13.45)	(33.82)	(26.10)	(18.90)
Two-year lagged term	-48.45**	-42.17**	-41.54***	-21.18	-50.32*	-66.24***
	(22.76)	(18.34)	(15.20)	(38.17)	(27.88)	(21.23)
The share of grid-days over 90°F						
Contemporaneous term	-123.6***	-126.6***	-130.1***	25.07	9.341	-1.462
	(43.13)	(43.65)	(44.20)	(57.28)	(59.07)	(61.16)
One-year lagged term	-11.02	-19.88	-35.07	53.31	34.15	13.93
	(40.14)	(40.98)	(42.44)	(44.28)	(43.32)	(42.80)
Two-year lagged term	-63.69	-76.06	-104.7**	60.67	30.91	-15.92
	(45.60)	(46.41)	(46.95)	(59.88)	(58.57)	(56.43)
Test H_0: Contemporaneous + lagged terms=0						
Rainfall	-127.69***	-96.18***	-81.19***	-271.35***	-235.26***	-189.17***
	(-3.72)	(-3.61)	(-4.00)	(-5.69)	(-6.51)	(-6.66)
Heat	-198.35**	-222.50**	-269.83***	139.07	74.40	-3.45
	(-2.33)	(-2.54)	(-2.96)	(1.52)	(0.84)	(-0.04)
Division FE	✓	✓	✓	✓	✓	✓
Constant	14.75***	16.61***	22.83***	26.50***	35.49***	48.45***
	(3.924)	(4.533)	(5.623)	(5.625)	(6.213)	(7.777)
Observations	322	322	322	322	322	322
R-squared	0.071	0.062	0.058	0.092	0.091	0.090

Note: Crop yield change is defined as the percentage difference between the yield and its predicted level acquired from each division's quadratic time-trend model. Division FE and robust standard errors are employed in all the regressions. Refer to the notes in Appendix Table A1 for the definition of the weather shock measures. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

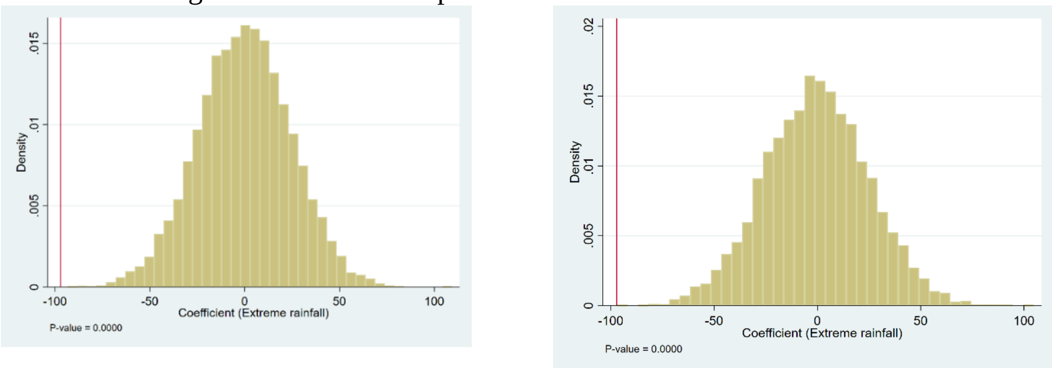
We also test the robustness of our main results in Appendix Table A2 using additional terms in the specification. In Appendix Table A3, we include one- and two-year lagged variables for the extreme rainfall measured at three different levels and for extreme heat above 90°F. The results show that the contemporaneous effects of extreme rainfall on yield change remain statistically significant when compared with Appendix Table A2. The lagged variables for extreme rainfall are mostly statistically significant. Extreme heat has a negative impact on the yield change of Aman rice, but not Aus rice. We also perform post-estimation tests to examine the cumulative effects of extreme weather on yield change for both Aman and Aus rice. The results in Appendix Table A3 suggest the cumulative effects of extreme rainfall on the yield change for Aman and Aus rice.

We examine if the main findings in Appendix Table A2 are spurious. Following Hsiang and Jina (2014) and Miller et al. (2021), we perform a falsification test by constructing false data where weather shocks are randomized across panel structures (i.e., grid-point and year), holding a dependent variable. We then re-estimate Equation (A1) using false data and compare the estimation results to the main findings in Appendix Table A2. The estimates from the false data should yield null results where the impacts of weather shocks on yield change is zero.

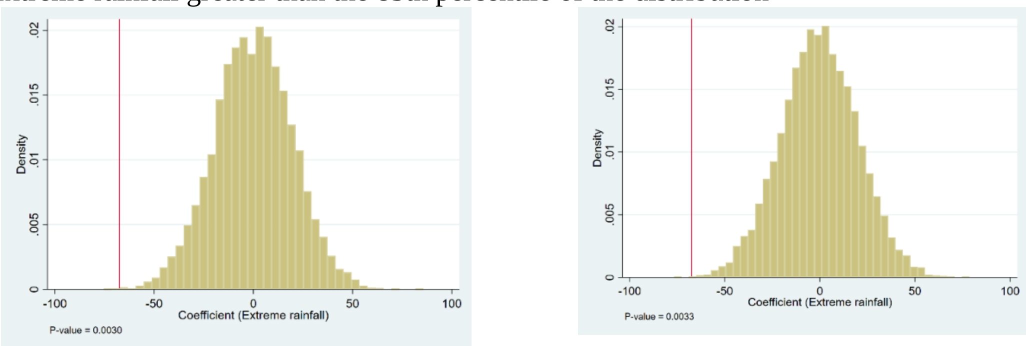
Moreover, two sets of false data are constructed for the test. In the first set of false data, which is named as "entire sample," weather shocks are randomized across panel structures, that is, division and year, 10,000 times without replacement for each level of extreme rainfall. In the second set of false data, which is named "within division," weather shocks are randomized across the year, 10,000 times without replacement for divisions and each level of extreme rainfall.

Entire sample Within division

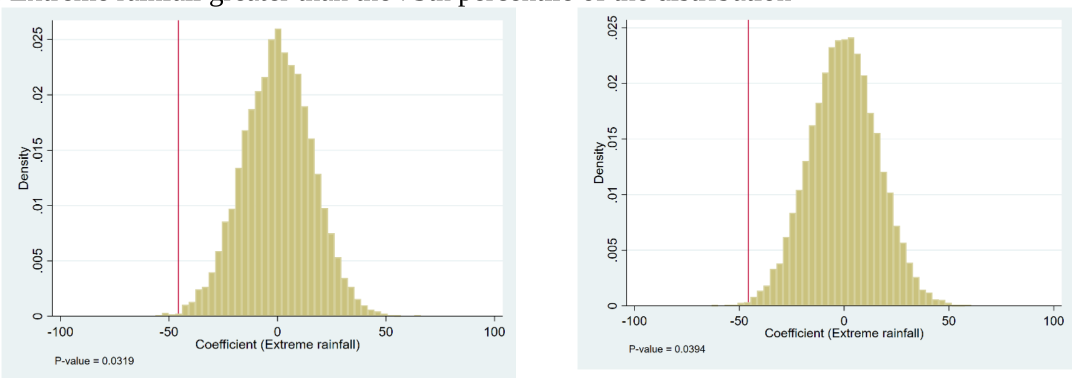
A. Extreme rainfall greater than the 90th percentile of the distribution



B. Extreme rainfall greater than the 85th percentile of the distribution



C. Extreme rainfall greater than the 75th percentile of the distribution

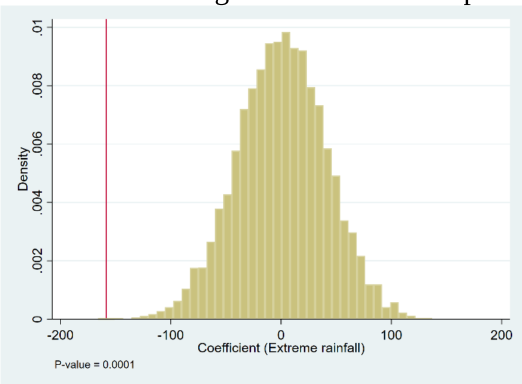


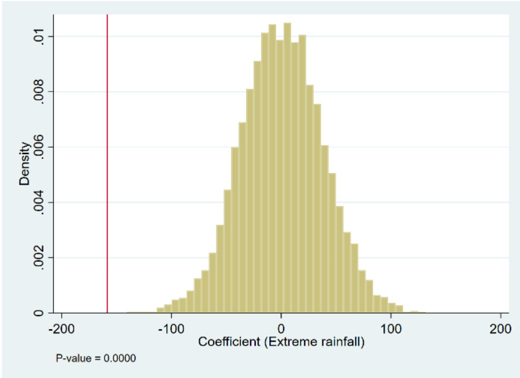
Appendix Figure A2. Falsification Test: Impacts of Extreme Rainfall on Yield Change for Aman Rice.

Notes: The null distributions of the coefficient of the extreme weather shock on the yield change for Aman rice are presented. Refer to the notes in Appendix Table A1 for the definition of the weather shock measures. Under false data for the entire sample, weather shocks are randomized across panel structures, that is, division and year, 10,000 times without replacement for each level of extreme rainfall. Under the false date for the within-division, weather shocks are randomized across years, 10,000 times without replacement for divisions and each level of extreme rainfall. The red vertical lines indicate the main estimates reported in Columns (1)–(3) of Appendix Table A2. P-values are reported at the bottom of each figure.

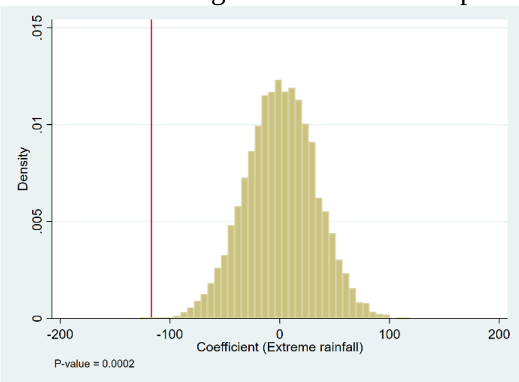
Entire sample Within division

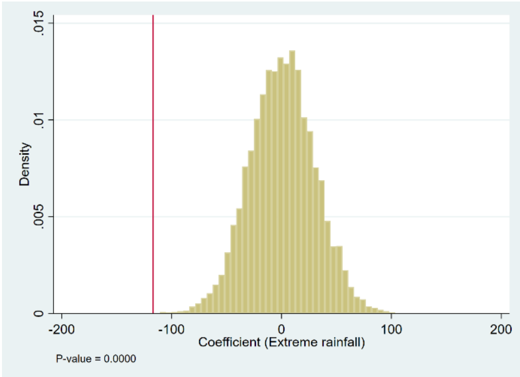
A. Extreme rainfall greater than the 90th percentile of the distribution



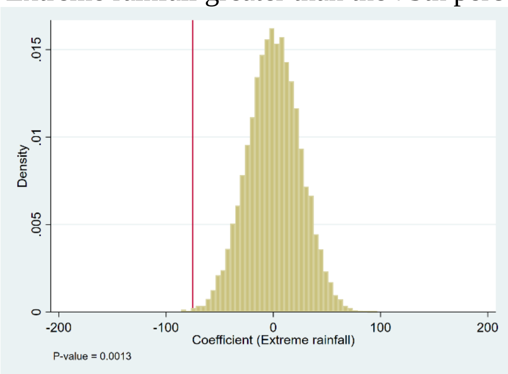


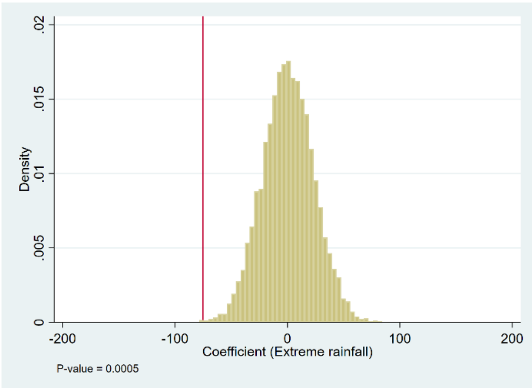
B. Extreme rainfall greater than the 85th percentile of the distribution





C. Extreme rainfall greater than the 75th percentile of the distribution





Appendix Figure A3. Falsification Test: Impacts of Extreme Rainfall on Yield Change for Aus Rice.

Notes: The null distributions of the coefficient of the extreme weather shock on the yield change for Aus rice are presented. Refer to the notes in Appendix Table A1 and Appendix Figure A2 for the measures of extreme rainfall and falsification test strategy. The red vertical lines indicate the main estimates reported in Columns (4)–(6) of Appendix Table A2. P-values are reported at the bottom of each figure.

Using two sets of false data, Appendix Figures A2 and A3 show the null distributions of the estimated β of Equation (A1), which capture the effect of extreme rainfall on the yield change of Aman and Aus rice, respectively. The red vertical lines indicate the main estimates presented in Appendix Table A2 for the three extreme rainfall levels. For easier comparison, the p-values of the main estimates from Appendix Table A2 are calculated using a randomized distribution from the false data. The p-values reported along with the distribution are extremely small, implying that the main findings reported in Appendix Table A2 are not spurious relationships between extreme rainfall and yield change.

Overall, the estimation results in this subsection show that the constructed measure of extreme rainfall harms the production of three major crops in Bangladesh over a long sample period, which validates the constructed measure.

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Appendix Table B1. Robustness Tests for Impacts of Extreme Weather on Early Marriage of Women.

Specifications/sample selection	(1)	(2)	(3)
Dependent variable: Marriage under the age of 18	Age in linear	Cluster within village	Extreme heat
The share of days that experienced rainfall greater than ___ of the distribution			
90th percentile	0.098*	0.108**	0.105*
	(0.055)	(0.054)	(0.055)
85th percentile	0.093**	0.108**	0.105**
	(0.045)	(0.045)	(0.046)
75th percentile	0.078**	0.095**	0.093**
	(0.039)	(0.038)	(0.041)
Observations	50,548	50,548	50,548

Notes: The sample contains females born between 1960 and 2004. Each entry reports the coefficient of the corresponding weather variable in each regression, using Equation (2). All regressions are controlled for birth year, age, grid, and division fixed effects except for Column (1). Column (1) for example, presents the coefficients of the weather variable from three different regressions using age in linear in the specification. The measures of extreme rainfall are defined as the share of days each grid-point experiences extreme rainfall over a year. The 90th, 85th, and 75th percentiles of the rainfall distribution are employed as the thresholds for extreme rainfall. Errors are clustered within each grid-point in all regressions to address the correlation among the error terms, except for Column (2), which is clustered within each village. Each grid-point size is 0.25 × 0.25-degree. All regressions are weighted by the population weights. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Appendix Table B2. Robustness Tests for Impacts of Extreme Weather on Early Childbirth for Women.

Specifications/sample selection	(1)		(2)		(3)	
Dependent variable: Childbirth under the age of 18	Age in linear		Cluster within village		Extreme heat	
The share of days that experienced rainfall greater than ___ of the distribution	In the year of marriage	In the year of childbirth	In the year of marriage	In the year of childbirth	In the year of marriage	In the year of childbirth
90th percentile	-0.415	0.409*	-0.415	0.409*	-0.295	0.277
	(0.308)	(0.242)	(0.308)	(0.242)	(0.306)	(0.237)
85th percentile	-0.529*	0.206	-0.381	0.144	-0.390	0.122
	(0.272)	(0.212)	(0.271)	(0.211)	(0.281)	(0.211)
75th percentile	-0.292	0.026	-0.179	-0.009	-0.186	-0.041
	(0.245)	(0.181)	(0.246)	(0.178)	(0.244)	(0.175)
Observations	5,465		5,465		5,465	

Notes: The sample contains females born between 1960 and 2004. Each entry reports the coefficient of the corresponding weather variable in each regression, using Equation (3). All regressions are controlled for birth year, age, grid, and division fixed effects except for Column (1). Column (1) for example, presents the coefficients of the weather variable from three different regressions using age in linear in the specification. Refer to the notes in Appendix Table B1 for the definition of the weather shock measures. Errors are clustered within each grid-point in all regressions to address the correlation among the error terms, except for Column (2), which is clustered within each village. Each grid-point size is 0.25 × 0.25-degree. All regressions are weighted by the population weights. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Appendix Table B3. Impacts of Extreme Rainfall on Early Marriage for Women by Marriage Cohort.

	Under the age of 18			Under the age of 15		
	(1)	(2)	(3)	(4)	(5)	(6)
The share of days experienced rainfall greater than __ percentile of the distribution	90th	85th	75th	90th	85th	75th
Extreme rainfall × 1970s Marriage cohort	2.064***	1.454***	0.912***	1.162***	0.852***	0.544***
	(0.075)	(0.044)	(0.023)	(0.083)	(0.053)	(0.029)
Extreme rainfall × 1980s Marriage cohort	1.696***	1.159***	0.719***	0.663***	0.457***	0.282***
	(0.044)	(0.027)	(0.014)	(0.051)	(0.034)	(0.019)
Extreme rainfall × 1990s Marriage cohort	1.539***	1.074***	0.672***	0.533***	0.372***	0.230***
	(0.039)	(0.023)	(0.012)	(0.040)	(0.026)	(0.015)
Extreme rainfall × 2000s Marriage cohort	1.280***	0.908***	0.578***	0.195***	0.136***	0.087***
	(0.033)	(0.020)	(0.010)	(0.023)	(0.016)	(0.010)
Extreme rainfall × 2010s Marriage cohort	1.124***	0.808***	0.522***	0.106***	0.069***	0.041***
	(0.045)	(0.026)	(0.014)	(0.023)	(0.015)	(0.009)
Constant	-0.093***	-0.107***	-0.122***	-0.056***	-0.067***	-0.077***
	(0.012)	(0.012)	(0.012)	(0.018)	(0.018)	(0.018)
F-statistics: H_0 is that all interaction terms are the same	50.64***	62.80***	81.48***	67.33***	84.54***	106.17***
Age at t(0)	9	9	9	9	9	9
Observations	50,548	50,548	50,548	37,764	37,764	37,764
R-squared	0.198	0.202	0.205	0.085	0.087	0.088
Birth Year FE	✓	✓	✓	✓	✓	✓
Age FE	✓	✓	✓	✓	✓	✓
Grid FE	✓	✓	✓	✓	✓	✓
Division FE	✓	✓	✓	✓	✓	✓

Notes: The sample contains females born between 1960 and 2004. All regressions are controlled for birth year, age, grid, and division FEs. Refer to the notes in Appendix Table B1 for the definition of the weather shock measures. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Appendix Table B4. Pairwise F-tests of Coefficients in Appendix Table B3.

	Under the age of 18			Under the age of 15		
	(1)	(2)	(3)	(4)	(5)	(6)
The share of days experienced rainfall greater than __ percentile of the distribution	90th	85th	75th	90th	85th	75th
Test H_0: Cohort1970 – cohort1980=0						
Difference in coefficients	0.367	0.295	0.193	0.499	0.395	0.261
F-statistics (significance)	23.736***	39.290***	60.912***	34.514***	50.339***	69.701***
Test H0: Cohort1980 – cohort1990=0						
Difference in coefficients	0.157	0.085	0.047	0.130	0.085	0.053
F-statistics (significance)	10.663***	8.107***	8.957***	4.496**	4.314**	4.762**
Test H0: Cohort1990 – cohort2000=0						
Difference in coefficients	0.259	0.166	0.094	0.338	0.236	0.143
F-statistics (significance)	49.359***	54.898***	58.517***	54.498***	59.626***	57.469***
Test H0: Cohort2000 – cohort2010=0						
Difference in coefficients	0.156	0.100	0.056	0.089	0.068	0.045
F-statistics (significance)	13.194***	15.417***	13.823***	7.768***	9.948***	11.695***

Note: The difference in the coefficients is shown in Appendix Table B3. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.