Groupe de Recherche en Économie
et Développement International

Cahier de recherche / Working Paper
23-05

Climate Change, Intimate Partner Violence, and the Moderating Effects of Climate Resilience Initiatives

Amanda GUIMBEAU
Xinde James JI
Nidhiya MENON

UNIVERSITÉ DE
SHERBROOKE

Climate Change, Intimate Partner Violence, and the Moderating Effects of Climate Resilience Initiatives*

Amanda Guimbeau [†], Xinde James Ji [††], and Nidhiya Menon[†]

Version: September 19, 2023

Abstract

This paper investigates the impact of climate change on women's agency in Bangladesh. Utilizing a novel dataset linking meteorological data with information on women's agency from the Bangladesh Demographic and Health Survey, and controlling for a variety of weather indicators in flexible specifications, we find that dry shocks increase tolerance for intimate partner violence among poorest women in agriculture-dependent communities, thus amplifying existing socio-environmental vulnerabilities. Climate resilience projects funded by the Bangladesh Climate Change Trust (BCCT) moderate the negative impacts of dry shocks on intimate partner violence, indicating an important role for initiatives that appear to have positive externalities in terms of ameliorating the harmful consequences of climate change on women. Our findings offer insights into the complex environmental and social dynamics that shape gendered climate change effects, and highlight the role of policy interventions in fostering resilience and women's wellbeing.

Key Words: Climate change; women's agency; intimate partner violence; adaptation, resilience, agriculture, Bangladesh

JEL Codes: Q54; J16; O13

Declarations of Interest: None

---

* We thank Sabikun Naher for excellent research assistance. The usual disclaimer applies. [†]Assistant Professor, Department of Economics, Université de Sherbrooke, QC, Canada. Email: Amanda.Guimbeau@usherbrooke.ca. [††]Assistant Professor, Food and Resource Economics Department, University of Florida, Gainesville, FL 32603, USA. Email: xji1@ufl.edu. [†]Professor, Department of Economics, MS 021, Brandeis University, Waltham, MA 02453, USA. Email: nmenon@brandeis.edu.

1. Introduction

Climate change impacts are not gender neutral. Women, especially those in developing nations, are disproportionately affected due to their extensive involvement in agriculture, existing political, social, and economic inequities, entrenched power dynamics, and gender-specific roles rooted in cultural norms (UNFCCC, 2023). The increased frequency and severity of extreme and unexpected weather events such as heatwaves, excessive rainfall and droughts, while impacting women's health, safety, and livelihoods, also have the potential of worsening underlying gender inequalities in vulnerable societies. This unequal burden faced by women is further amplified by their limited access to resources for relief and recovery. In developing countries where women's economic stability is significantly tied to the agricultural sector, environmental anomalies could act as a "threat multiplier" through channels of lost income as well as intra-family dynamics (UN Women, 2022), intensifying susceptibilities to gender-based violence.

Although the existing literature illustrates the diverse implications of climate shocks on outcomes in developing country settings, for example agriculture and livelihood (Aragon et al. 2021), mortality (Burgess et al. 2017, Banerjee and Maharaj 2020), labor allocation (Liu et al. 2023), or inter-personal conflict (Hsiang et al. 2013), a thorough assessment of the gender-differentiated impacts of climate change and how that manifests through existing social-economic and cultural inequalities remains relatively unexamined. At the same time, communities, policy-makers, and international agencies strive to find effective ways to buffer the impacts of climate change, including providing access to cooling technology (Deschenes and Greenstone 2011), healthcare (Banerjee and Maharaj 2020, Mullins and White 2020), or land tenure reform (Ajefu and Abiona 2020). But the extent to which these efforts mitigate the deleterious impacts of climate change, especially amongst at-risk populations, remains unclear.

In light of these considerations, the objective of this paper is twofold. First, we quantify the effects of climate shocks on women's attitudes towards intimate partner violence (IPV) and other agency measures, and document the extent to which these effects diverges across existing environmental and socio-economic vulnerabilities. Our empirical analyses focus on Bangladesh, a developing country that is amongst the most susceptible. The World Bank (2022) estimated that climate variability and extreme weather events in Bangladesh could lead to a potential loss of one third of its agricultural GDP by 2050. With nearly 40% of the population directly employed in agriculture, livelihoods are inherently linked to weather fluctuations. At the same time, the incidence of intimate partner violence (IPV) in Bangladesh is alarming, with 73% of ever-married women experiencing one or more forms of IPV at least once in their lifetime (Bangladesh Bureau of Statistics, 2016). On the flip side, over one-third of men aged between 15-49 agree that wife-beating is justified for several reasons (DHS, 2007). Our analysis seeks to unravel the nuanced effects of climate-induced environmental risks on women.

Second, we identify initiatives that attenuate these negative impacts. During our study period, the Bangladeshi government implemented The Bangladesh Climate Change Trust (BCCT), a nationally funded scheme that reflects the Bangladeshi government's commitment to foster climate resilience. The BCCT financed community-based projects that promote climate adaptation and resilience, with a fraction of projects being directly women-centric. We evaluate how effective these BCCT projects are at attenuating the harmful impacts of climate shocks on women's wellbeing.

We accomplish these objectives by constructing a novel dataset linking gridded data on rainfall, temperature, other climatic variables, and individual-level data on women's agency. We obtain geo-referenced monthly meteorological data at a spatial resolution of $0.1^{\circ} \times 0.1^{\circ}$ spanning

1980-2020 from the Copernicus Climate Change Service. We combine this data with women's empowerment indicators, including perspectives on and experiences of IPV, participation in decision-making, and control over personal earnings from four waves of the Bangladesh Demographic and Health Surveys (BDHS). Our empirical strategy leverages a fixed-effect design that controls for unobserved heterogeneity, regional trends, and location-specific seasonality. We follow the climate impact literature (Burgess et al. 2014, Hsiang et al. 2013, Iyer and Topalova 2014, Tsaneva 2020) to construct standardized measures of climate shocks, defined as deviations from the historical cluster-specific average in a given month. Our main variable of interest is a drought metric that counts the cumulative number of months over the three years prior to the survey month wherein rainfall realization was at least one standard deviation below the historical monthly averages (the magnitude of this shock is consistent with other recent studies such as Abiona and Foureaux-Koppensteiner 2018), calculated using the benchmark period 1980-2000. We construct similar intensity variables for months of wet spell and for months of heat waves. We further include a vector of individual and household characteristics, and contemporaneous weather variables as controls.

Our analysis indicates that a higher frequency of dry months leads to greater acceptance of IPV by women (which is strongly correlated with experience of IPV as noted in Uthman et al. 2011, Titilayo et al. 2013, and Bengesai and Khan 2023). Examining effects more closely, while the impact on the average Bangladeshi women is insignificant, drought increases tolerance for IPV for two groups of women: those who live in agriculture-dependent communities, and those who possess less wealth. A one-standard-deviation increase in the frequency of dry months raises the likelihood by 4.3 percentage points that women in the lowest wealth quintile agree that wife-beating is justified for at least one of the reasons noted in the survey. For women in agriculture-dependent communities, this increase is 2.5 percentage points. There are few measurable effects for wet or hot months. These results withstand several robustness checks and heterogeneity analyses reveal that drought has larger negative impacts (more acceptance of IPV) on the poorest women in agriculture-dependent communities.

Our second goal is to evaluate whether climate-resilience initiatives mitigate the negative impacts of environmental shocks. We digitized the list of approved and finalized BCCT projects from official sources, including the location (at the *upazila* level) and timing of those projects. Our results indicate that proximity to a BCCT project completely counteracts the effect of droughts in agricultural communities as across all wealth strata; the negative impact of droughts on IPV becomes insignificant if the respondent lives near a BCCT project. These results remain even after we control for a host of pre-treatment covariates, and possible endogeneity in aid project location. Placebo tests find no significant attenuation effects for inactive (past or future) BCCT projects, and significant but smaller effects for other development assistance projects. Further analysis suggests that active BCCT projects play a key role in improving women's welfare through access to media, transport facilities, electricity, and cash earnings.

Our paper makes three contributions. First, we complement the literature on the inequitable socio-economic impact of climate change in developing nations. Prior literature has shown differentiated impacts on mortality (Burgess et al. 2017, Banerjee and Maharaj 2020, Deschenes and Greenstone 2011, Geruso and Spears 2018), human capital (Garg et al. 2020, Maccini and Yang 2009, Shah and Steinberg 2017), labor reallocation (Liu et al. 2023), and inter-personal conflicts (Hsiang et al. 2013, Ubilava et al. 2022, Maconga 2023). We add to this literature by documenting how climate change worsens gender inequalities, specifically for poor agriculture-dependent women.

Second, our work builds on existing literature on gender equality and women's agency in the developing world more broadly (Guimbeau et al. 2023, Hossain et al. 2022, Schneider et al. 2016, Sekhri and Hossain 2023). Importantly, in evaluating climate variables, our study considers weather variables in unison. This is important since factors such as temperature and rainfall are likely correlated, hence focusing on one or the other could lead to biased inference. For instance, prior work has documented effects of rainfall shocks alone on dowry deaths (Sekhri and Storeygard 2014), or rainfall shocks alone on domestic violence (Abiona and Foureaux-Koppensteiner 2018, Cools et al. 2020, Diaz and Saldarriaga 2023, Epstein et al. 2020). Consistent with recent developments in the literature (Hanifi et al. 2022), we consider temperature and rainfall jointly while allowing for more flexible functional forms (non-parametric specifications as well as quadratic forms). Our results substantiate that factors such as income uncertainty can increase IPV.

Third, our work contributes to policy debates on mechanisms that mitigate climate impacts (Ajefu and Abiona 2020, Barreca et al. 2016, Cohen and Dechezleprêtre 2017, Colmer and Doleac 2023, Isen et al. 2017, Mullins and White 2020, Nguyen et al. 2022, Randazzo et al. 2023, Sarsons 2015, Rustad et al. 2020). Several studies have assessed the mitigating impact of the NREGA workfare program in India on factors such as crime, conflicts, academic performance, sex ratios, domestic violence, long-term health, and mortality (Banerjee and Maharaj 2020, Dasgupta 2017, Fetzer 2020, Garg et al. 2020, Iyer and Topalova 2014). Other research has highlighted the value of cash transfers in enhancing resilience in Nicaragua (Macours et al. 2022), and reducing losses in Bangladesh (Pople et al. 2023). The novelty of our study is that it evaluates the impact of a specific climate-resilience initiative which was designed to reduce vulnerability to climate change. To the best of our knowledge, our paper is the first to analyze empirically the effectiveness of climate-aid funds that involve both proactive and reactive adaption and resilience strategies. Our findings that the detrimental effects of dry shocks on women's attitudes towards IPV are essentially nullified in the vicinity of climate projects underlines that such policies have positive spillover effects well beyond increasing adaptation and resilience.

2. Background and data

Bangladesh is one of the largest populations at risk from the impacts of climate change. Despite being responsible for only 0.56% of global $C0_2$ emissions (Hasan and Chongbo 2020), it ranks as the seventh most vulnerable country to climate-related disasters.[1] Bangladesh's vulnerability is amplified by its geographical location, characterized by a flat deltaic topography. Consequently, various parts of the country frequently face floods, droughts, strong cyclones, and the intrusion of saline water into freshwater sources. These factors disproportionately affect vulnerable communities given the relatively high incidence of poverty, high population density, and heavy reliance on agriculture. Moreover, climate change exacerbates existing gender inequalities, imposing additional burdens on women. It displaces them and their families, diminishes their opportunities for financial independence, and thus undermines hard-won achievements made in bridging gender gaps.

2.1. Gender roles, women's agency, and experience of domestic violence

We use individual-level data from four rounds of the BDHS from 2007, 2011, 2014, and 2017. These are two-stage nationally representative samples like other Demographic and Health Surveys.[2] We build a pooled cross-sectional dataset, and use the geographic coordinates of each surveyed cluster across rounds to merge with the geo-coded climate data. Figure 1 shows the location of BDHS clusters in 2007 (on the left), and for the three other years (on the right).

[1] See the Global Climate Risk Index (CRI) of 2021 by Greenwatch.
[2] Bangladesh has 8 administrative divisions: Barishal, Chattogram, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur and Sylhet. Each division is further divided into *zilas* and *zilas* in turn contain *upazilas*.

2.1.1. Women's attitude towards domestic violence

We use samples of women aged 15-49 from 2011, 2014, and 2017 waves and obtain detailed information on individual and household characteristics. These samples are also used to construct our outcomes of interest pertaining to gender attitudes, women's agency, and experience of IPV.[3]

We begin by using variables related to attitudes towards wife-beating. These act as proxies for women's perception of their own status (NIPORT 2013), while also proxying for other dimensions of women's status (including self-esteem, sense of empowerment and entitlement) with various implications for wellbeing. Married women aged 15-49 across these three years were asked whether they agreed that beating is justified if the wife (i) burns food; (ii) argues with him; (iii) goes out without telling him; (iv) neglects the children; (v) refuses to have sexual intercourse with him. We create an index dummy variable that equals 1 if the woman agrees with at least one of these five statements.

2.1.2. Experience of domestic violence

We use the domestic violence module available only in the 2007 BDHS to measure the experience of spousal violence. This sample provides information on whether ever-married women had ever experienced physical or sexual abuse committed by their husbands.[4] The questionnaire was administered to only one eligible respondent per household. There were 4,467 ever-married women and 3,374 ever-married men eligible to respond, and several measures were taken to

[3]The 2007 BDHS round also assessed women's attitudes towards domestic violence. However, there was a distinct difference in one of the statements concerning when beating is deemed acceptable. To ensure consistency, our analysis focuses solely on the sample of women who were interviewed in 2011, 2014, and 2017. Nevertheless, since the 2007 wave is the only round that captures information on experiences of domestic violence, we use this data separately to construct variables pertaining to actual exposure to domestic violence. The results from this sample are also reported separately.

[4] The survey measured domestic violence using a shortened and modified Conflict Tactics Scale (CTS) which is considered to be more effective at reducing under-reporting compared to alternative datasets on domestic violence (see Cools et al. 2020, Kishor 2005, La Mattina 2013).

safeguard their privacy while answering the IPV questions.[5]. We restrict our analysis to currently married women who are non-visitors. We code dependent variables for the experience of physical and/or sexual violence, similar to responses on questions relating to acceptance of IPV described above.[6]

2.2. Weather variables

We use data from the Copernicus Climate Change Service, focusing on the agrometeorological indicators from 1980 to obtain gridded monthly meteorological data at a spatial resolution of 0.1^0 x 0.1^0.[7] The dataset provides several climatic variables including temperature, precipitation, vapor pressure, wind speed, solar radiation flux, amongst others. Using a subset of this weather data, we construct monthly averages for these variables since other features of weather are likely to be correlated with both our outcomes and our selected climatic variables of interest.[8] We match the latitude-longitude of each sampled cluster over DHS rounds to the geo-coded weather data.

We use inverse-distance matching to obtain local measures of climate through gridded climatic observations. For each DHS cluster, we calculate the weighted average of the climatic

---

[5] In adherence to WHO's ethical and safety guidelines for domestic violence research, the 2007 BDHS implemented multiple measures to ensure privacy: (1) Only one eligible respondent per household was selected to safeguard their privacy and keep the nature of the questions confidential from other household members; (2) Respondents were informed about the sensitivity of the upcoming questions and reassured about the confidentiality of their answers; (3) The domestic violence section was conducted only if the respondent's privacy could be ensured; otherwise, it was omitted, and the circumstances documented. Additionally, interviewers received specialized training to develop the necessary skills for collecting domestic violence data confidentially and ethically.

[6] A currently married woman is considered to have experienced intimate partner violence if she answers yes to any of the following questions: Does your husband ever do any of the following things to you: (a) push you, shake you, or throw something at you; (b) slap you; (c) twist your arm or pull your hair; (d) punch you with his fist or with something that could hurt you; (e) kick you, drag you, or beat you up; (f) try to choke or burn you on purpose; (g) threaten or attack you with a knife, gun, or any other weapon? For the prevalence of sexual violence, we use a binary measure that equals one if she answers yes to the statement "does your husband ever physically force you to have sexual intercourse with him even when you did not want to?"

[7] This dataset is also referred to as AgERA5 and is based on the hourly ECMWF ERA5 at surface level. The original file format is the Network Common Data Form (NetCDF-4). To obtain month-year level data from 1980 onwards, we process these files in Python.

[8] The distributions of these additional variables are also likely to be affected by climate change, hence it is important to control for them.

metric from the 5 closest grid points, weighing each point by the inverse of the distance from the cluster's location. This approach is commonly used in the environmental economics literature (Mendelsohn et al. 1994, Deschenes and Greenstone 2011, Zhang et al. 2017). We ensure robustness to use of 1, 3, and 10 closest grid points.

2.2.1. Evidence of climate change

Figure 2 demonstrates kernel densities for temperature, rainfall, and vapor pressure for different time periods. Consistent with Zhang et al. (2017), we note a right-ward shift in the distribution of temperature over time, confirming a significant shift in weather patterns over time. This is the case in Figure 2 (a) when we consider the distributions for the two decades, 1980-1990 and 2010-2020, and in Figure 2 (b) when we consider two different periods, 1980-1999 and 2000-2019. In Figure 2 (c), the kernel density plot indicates that climate change also changes the distribution of other climatic variables such as vapor pressure. In the subsequent panels, we focus on the distributions of maximum temperature and rainfall during the critical monsoon season, a period where climate change is modifying normal weather patterns and significantly affecting agricultural yields. In Figure 2 (d), we present the distribution of maximum temperature calculated as annual averages using monthly values for the monsoon period, June through October, given that temperature in these months varies (from the rest of the year) with the arrival of the monsoon. Again, there is a noticeable change in the distribution of average maximum temperature. In Figures 2 (e) and 2 (f), we present the distributions of average annual monsoon rainfall. Again, shifts are evident.[9]

[9] During the monsoon season, the weather generally stays warm, although there are occasional cooler days when there is heavy rainfall. Data analyses indicate a steady rise in temperatures throughout this period, with the average maximum and minimum temperatures each monsoon season increasing at a rate of 0.05^0C and 0.03^0C, respectively. (Source: Climate Change Knowledge Portal: Bangladesh, World Bank. Accessed on 26 August 2023).

However, changes in climatic variables have not been uniform throughout Bangladesh. There is heterogeneity across districts in terms of frequent and intense floods, prolonged dry spells, longer summers and/or warmer winters. There is also evidence of declining monthly mean rainfall from June to August (the peak monsoon), while September's and October's mean monthly rainfall values have increased, signaling that the monsoon period is extending as climate evolves (World Bank, 2021).[10] Further, coastal communities are particularly vulnerable to increased salt-water intrusion and coastal flooding due to sea-level rise.

2.3. Other data

In addition to the individual and household level characteristics as well as the weather data, we complement our research with information from other official sources. These additional datasets include information on climate-resilient projects, climate vulnerability indices, pre-treatment geographic and socio-economic covariates at the sub-district level, and other empowerment markers. We provide detailed explanations below.

2.4. Summary statistics

Table 1 presents the summary statistics for the full sample of women aged 15-49 years. In Panel A, we note that 27% of women agree that spousal abuse is justified for at least one reason. Concurrently, 17% do not participate at all in decision-making processes, while 67% have the freedom to visit health centers alone or with children. 57% report having control over their own earnings. Turning to Panel B, within the past year, 19% and 11% of respondents have endured physical and sexual violence, respectively. About one in four women reported frequent or occasional experiences of physical and/or sexual violence in the same timeframe, with 6%

[10] "*Climate Change in Bangladesh: Impact on Infectious Diseases and Mental Health*", World Bank, 2021. More information can be obtained here: https://www.worldbank.org/en/news/feature/2021/10/07/climate-change-in-bangladesh-impact-on-infectious-diseases-and-mental-health.

enduring both types of violence. In Panel C, we note that there was on average 5.7 "dry" months in the three years preceding the survey, with a standard deviation of 2.5 months. The average number of "wet" months is 4.42, with a standard deviation of 1.7 months.[11] Panel D shows the statistics for the set of controls used in all our regressions.

3. Empirical strategy

We measure the exposure of households to weather fluctuations, based on their localized clusters and survey month and year. In constructing weather shocks, we follow the related literature and consider the deviations of rainfall and temperature from their long-run local averages, defined over the period 1980 and 2000, adjusting for historical standard deviation. These weather-related shocks are often defined as extreme weather events that deviate significantly from the long-term average, and can be considered as random draws from their respective distributions (Dell et al. 2014, Ibanez et al. 2021).

We define a negative rainfall shock (drought) variable for a given month as a binary variable that takes a value of one if the rainfall in that month is equal to or below the cluster-specific norm by at least one standard deviation, and zero otherwise. Cluster-specific norms are defined as the 20-year cluster-average level of rainfall for that month. Similarly, we identify a heat shock as when the actual monthly average temperature was equal to or greater than 1 SD above the 20-year cluster-level average for that month, and an excessive rain shock as when the actual monthly rainfall exceeds the 20-year cluster-level average for that month. As stated above, the choice of 1 SD is consistent with other recent studies (Dell et al. 2014, Abiona and Foureaux-Koppensteiner 2018, Ibanez et al. 2021).

[11] This is consistent with Tsaneva (2020). That study finds an average number of dry months for 12 months before survey of 1.22 with a SD of 1.21 (based on historical distribution for 1950-1999). We obtain an average of 1.68 with a SD of 1.05. There were several months when rainfall was below the long-term average, but not by a standard deviation (given our historical distribution of 1980-2000). The maximum number of dry months in our data is 13.

Our key objective is to investigate the impact of weather shocks on women's agency. We follow Hsiang et al. (2013), Burgess et al. (2014), Iyer and Topalova (2014), and Tsaneva (2020) to define our main explanatory variable as the number of months during the past 3 years (36 months) in which weather shocks (drought, excessive rain, or extreme heat) occurred.[12] We begin by estimating equation (1) to explore the effects of climate on women's attitude towards IPV:

$$y_{icdmt} = \beta numdrymths_{cdmt_{-36}} + \gamma W_{cdmt} + \theta X_{icdmt} + \alpha_d + \eta_m + \lambda_t + \omega_{dm} + \mu_{dt} + \epsilon_{icdmt} \quad (1)$$

where y_{icdmt} represents the outcome of interest for woman *i* surveyed in cluster *c* in district *d* in month *m* and year *t*. For our main specification, y_{icdmt} is a dummy variable that takes a value of 1 if the respondent agrees with at least one of the five statements pertaining to situations in which wife beating is justified. The variable of interest, $numdrymths_{cdmt_{-36}}$, is the cumulative number of months over the 3 years prior to the survey month in which rainfall realization was least 1 SD below the historical monthly average (calculated over 1980-2000). W_{cdmt} is a vector of other climatic conditions that includes the number of wet shocks during the past three years, and the number of months with temperature shocks. This vector also includes climate variables at the time of the survey. In all models, we allow temperature to vary non-parametrically in the month and year of survey by including dummy variables for temperature bins constructed using daily average temperature, and representing the number of days of each month that fall within each 5^0C interval: $(10-15]^0C$, $(15-20]^0C$, $(25-30]^0C$, and $(30-35]^0C$.[13] The omitted temperature bin is

[12] We choose to consider the number of months with weather shocks within the past 3 years instead of 12 months prior to the survey year for two reasons. First, we need an adequate time frame for the occurrence of climate shocks to potentially affect women's attitudes towards domestic violence and other empowerment indicators. Second, we limit the time interval as adaptive responses may become important in the absence of an upper time bound.

[13] The binning approach is recommended in the weather-economics literature to obtain more precision for the intensity of heat exposure, and to account for the possible nonlinearities in the effects of weather on outcomes of interest (Zhang et al. 2017, Burke et al. 2015, Blom et al. 2022, Hanifi et al. 2022).

$(20-25]^0C$, which is considered to be "comfortable". We also include rainfall in the month and year of survey in a quadratic form. The vector of climatic variables W_{cdmt} takes the following form:

$$W_{cdmt} = \tau numwetmths_{cdmt_{-36}} + \phi numhotmths_{cdmt_{-36}} +$$

$$\sum \alpha^N temp^N_{cdmt} + \delta_1 rain_{cdmt} + \delta_2 rain^2_{cdmt} \qquad (2)$$

Returning to equation (1), X_{icdmt} is a vector of controls for individual and household characteristics including the respondent's and partner's age, a dummy for rural communities, woman's and her husband's highest level of education, age at first cohabitation, religion, and the number of young living children (below the age of 5) in the household.

Equation (1) also includes a set of temporal and spatial fixed-effects. The use of district fixed-effects (α_d) allows us to control for local regional characteristics including cultural norms pertaining to attitudes towards women's role in the economy and at home, and other institutional factors. This means that our estimates are identified from within-district variation in weather changes. The term η_m represents survey-month fixed-effects that account for seasonal variation. We also use survey-year fixed-effects, λ_t, to control for time-specific shocks affecting all districts in a specific survey year. District-by-month fixed-effects, ω_{dm} , and district-by-year fixed-effects, μ_{dt}, account for temporal variations across districts including local seasonality and regional trends. The error term is ϵ_{icdmt}. We report weighted regressions and robust standard errors clustered at the DHS cluster level.

The identifying assumption for our parameter of interest, β, is that conditional on the controls for contemporaneous weather, location-specific seasonality, and on other variables in the model, there are no omitted variables that are correlated with both the number of dry months in the 3 years prior to the survey year and with women's attitudes towards IPV. Weather shocks are as good as random in this case.

4. Droughts increase women's acceptance of IPV

4.1. The impact of weather shocks on acceptance of IPV

We first present our headline result of how weather shocks affect women's acceptance to IPV. Table 2 presents the results from the main regression in equation (1). Column (1) presents results from the full sample and shows statistically non-significant impact of drought on women's attitudes towards IPV. Columns (2) and (3) estimate effects by partitioning the sample on indicator variables for above and below median values (based on each sample distribution) for the share of employment in agriculture at the *upazila* (sub-district) level, which we call "agricultural-dependent" and "non-agricultural-dependent" communities, respectively. We find that in agricultural-dependent communities, women's acceptance of IPV is higher if the community experienced drought in the past 3 years. A 1 SD increase in the frequency of dry months raises the probability of IPV acceptance by approximately 2.5 percentage points for women belonging to households in agriculture-dependent communities.[14] In communities not dependent on agriculture, we find no effect. We also find no significant effect of higher frequencies of wet and hot months for both samples.[15]

[14] Research indicates a strong positive correlation between the tolerance of IPV and the actual experience of abuse. Uthman et al. (2011), for example, examine the relationship between individual and community acceptance of IPV and its occurrence by analyzing data for over 8,000 couples in Nigeria. They find that women with more tolerant attitudes towards IPV were more likely to report experiencing spousal abuse. Similarly, Titilayo et al. (2013) identify a significant positive correlation between women's attitudes towards IPV and the incidence of domestic violence in Nigeria. They argue that promoting a shift in women's attitudes towards zero tolerance of gender-based violence could significantly contribute to protecting women from IPV. A study conducted by Bengesai and Khan (2023) for Malawi, Zambia, and Zimbabwe, reveals that the risk of experiencing IPV doubles when both partners condone wife-beating. They conclude that attitudes towards violence are potentially one of the most crucial indicators of IPV prevalence.

[15] In a methodological framework similar to ours, Tsaneva (2020) documents that a higher number of dry months in a given year is associated with increases in the probability of child marriage. The study also finds that higher

We then break down the sample by respondents' wealth in columns (4)-(6). We find that these vulnerable households are the most affected, and the magnitude of the impact rises with the extent of vulnerability. An additional dry month increases the probability of justifying IPV by 0.9 percentage points for women with wealth in the three lowest quintiles, and approximately 1.6 percentage points for women in the lowest wealth quintile. That is, a 1 SD increase in the frequency of dry months increases acceptance of IPV by 2.4 percentage points for women in the three lowest wealth quintiles, but 4.3 percentage points for women in the poorest quintile. We again do not find significant impacts of higher frequencies of wet and hot months on acceptance of IPV.

4.2. Robustness tests for the main results

4.2.1 Alternative specifications and additional controls

We consider additional checks in Table A1 to ascertain the robustness of these results. In Panel A, the results remain qualitatively similar when we use the log number of dry months in the 3 years prior to survey. To address population sorting that could be partly driven by climate shocks, we control for the number of years the respondent has lived in the current residence in Panel B. Our estimates remain for agricultural-dependent communities and for respondents in the three poorest quintiles, while increasing in magnitude as compared to Table 2. When we restrict our sample to the poorest women who have been living in the current place of residence for more than 15 years (the median number of years of residence), we continue to obtain a positive association

---

frequencies of wet months and of hot months do not impact the probability of early marriage significantly. Studying the response of dowry deaths to weather variability in India, Sekhri and Storeygard (2014) find that plausibly exogenous rainfall shocks indeed impact dowry deaths but that wet shocks have no apparent effect. Lee (2016), employing a linear probability model finds that variability in prior year's growing degree days (GDD) and rainfall in both the current and previous year significantly influences women's perspectives on domestic violence for a group of 38 countries. Abiona and Foureaux-Koppensteiner (2018), in their analysis of household shocks on domestic violence in Tanzania also find no impact of wet shocks on the incidence of domestic violence. Sekhri and Hossain (2023) documenting the association between groundwater scarcity and sexual violence against women find that negative groundwater shocks (defined as variations from the long-term average in subsurface water availability) are correlated with an uptick in the number of reported rape cases, while positive groundwater shocks have no significant effects.

that is measured without error between the number of dry months and the dependent variable.[16] In Panel C, we replace our variable of interest with exposure to quartiles of dry shocks.[17] We find that related to the lower quartile (omitted category), exposure to higher quartiles of dry shocks results in larger effects and these impacts are precisely measured in agriculture dependent communities and for households in the lower wealth quintiles.

In Table A2, we control for three additional weather-related controls including solar radiation, wind speed, and vapor pressure, averaged over the three years prior to survey year. The main results in Table 2 remain unaltered.

4.2.2. Monsoon rainfall and growing degree days (GDD)

Approximately 70-85% of the annual rainfall is received in the monsoon months of June to October in Bangladesh, and heavy rainfall during this period is critical to the country's agriculture. As an additional robustness check, we construct another measure that captures low monsoon rainfall occurrences. We follow an approach similar to Afridi et al. (2022). To define a drought shock for a specific year, we calculate the total cluster-specific rainfall for the monsoon months. We then compare this yearly average with the long-run monsoon rainfall average (using the 20-year period of 1980-2000). A rainfall shock is defined to occur if the monsoon rainfall in a given year is at least one SD below this long-term average. We then code a binary variable that takes a value of one if the cluster has experienced a monsoon drought shock at least once over the past 3 years.

To capture the nonlinear effects of higher temperatures on agriculture, we construct GDD following standard meteorological procedures based on Baskerville and Emin (1969) and Snyder

[16] The variable measuring the number of years lived in the current place of residence is available only in 2017. Thus, results in Panel B are restricted to these data.
[17] In the lowest quintile sample, the lower quartile: ≤ 3 months, second quartile: 3-5 months, third quartile: 5-7 months, and for the top quartile: > 7 months.

(1985), using a threshold of 30^0C. Our main results are robust to the inclusion of monsoon drought shocks and GDD.

4.2.3. Heterogeneous effects

In Table 3, we perform heterogeneity analyses for the lowest wealth quintile of households.[18] We select three key variables to construct our samples – sectoral area of residence, literacy status, and economic prosperity as measured by nightlights. These are factors that could potentially mitigate the main effects documented above. Columns (1) and (2) present the results from separate regressions for rural and urban areas. As anticipated, women in rural areas are relatively more affected by dry shocks, possibly because their income predominantly comes from agriculture which is especially vulnerable to insufficient rain.

In columns (3) and (4), we split the sample according to literacy status. Given that education is often instrumental in these contexts, we would expect educated women to be less affected to weather shocks. We find that the main effects indeed vary with literacy status – the effect is pronounced among illiterate respondents.

Finally, we check whether effects vary across levels of economic prosperity. These results would also help shed light on a key mechanism potentially in play – the reduction in women's agency might be due to a decrease in economic activity which influences the outcome through effects on income. We use satellite data on cluster-specific nighttime light intensity in the survey year as a measure for local economic activity (Henderson et al. 2012). We then classify respondents into high or low prosperity areas based on whether light intensity is above or below the 50th percentile of the distribution. Consistent with our findings in columns (1) and (2), there is a significant detrimental impact of dry months in less prosperous clusters.

[18] Results for the other sub-samples are available upon request.

4.2.4. Effects by decade of birth

We next consider heterogeneity by cohorts. We augment equation (1) with indicators for women's birth decades, and separate interaction terms for the frequency of dry months and each birth cohort while controlling for cohort-specific effects from excessive rain (wet shocks) and heat (high temperature shocks) as before. The interaction terms are thus $numdrymths_{cdmt_{-36}} \times cohort_b$, $numwetmths_{cdmt_{-36}} \times cohort_b$ and $numhotmths_{cdmt_{-36}} \times cohort_b$. We report the net effect of droughts for each cohort, with respective F-statistics and associated *p*-values in square brackets.

Results are presented in Table 4. We find that while women's acceptability of IPV across all birth decades are impacted by dry shocks, the effects are relatively more pronounced for women born in later cohorts in the poorest households. For instance, we find that the total effect for women born in the 1980s and 1990s has larger magnitudes compared to women born in the 1960s. Referring to the total effect for those born in the 1980s in column (6), we find that an additional dry month leads to a significant increase of 2.5 percentage points in IPV acceptance. The frequency of dry months is also positively associated with the acceptability of wife-beating among the earlier cohorts, but the total effects are not significantly different from zero.

With changing gender norms, greater access to education, digital technology, and supportive networks providing scope for enhanced adaptive capacity, we would, *a priori*, expect differential impacts of smaller magnitudes for younger women. The effects presented in this section do not support this assertion. Intersecting factors that could explain these results for younger women include the increasing frequency and severity of climate shocks in Bangladesh and the susceptibility of younger women to these shocks, as well as traditional gender roles that place younger women at a disadvantage as compared to older women.[19]

4.3. Wealth and agriculture dependency

We examine whether wealth and agriculture dependency compound each other when communities experience drought. In Panels A and B of Table 5, we present results where the samples are partitioned based on both wealth strata and the share of employment in agriculture at the *upazila* (sub-district) level. In Panel A, we find that poorer women living in agriculture-dependent communities are even more likely to justify IPV when dry spells increase. For instance, a unit increase in the number of dry months increases tolerance of IPV by 3.1 percentage points for the lowest quintile in agriculture dependent communities. This is in contrast to the 1.0 percentage point effect in column (1) that does not condition on wealth. There are no impacts in Panel B that considers communities that are not dependent on agricultural employment.

To further pin down how climate vulnerability and existing socio-economic divides compound each other, we digitize *upazila*-level data on climate vulnerability indices from the "Nationwide Climate Vulnerability Assessment in Bangladesh," an official report published by the Bangladeshi Ministry of Environment, Forest, and Climate Change.[20] We construct indicators measuring the degree of agricultural vulnerability to climate change, and code a variable that takes a value of 1 if the cluster belongs to a sub-district in the highest quartile. We accomplish this by calculating a composite index made up of the following three components: crop yield vulnerability,

[19] This coincides with Guimbeau et al. (2023) which studied proximity to mining operations and acceptance of IPV in India. That study also found that younger women are more susceptible compared to older women.

[20] This report is a publication of the Ministry of Environment, Forest, and Climate Change (Government of the People's Republic of Bangladesh) and GIZ (*Deutsche Gesellschaft fur Internationale Zusammenarbeit*). It was published in 2018 and contains rich information on climate vulnerability (current and future), adaptive capacity, and impact chain analysis. A list of 12 vulnerability indices constructed using a 30-year average climate data since 1980 is available for each sub-district. The index ranges from 0 (no vulnerability) to 1 (highly vulnerable). Current vulnerability assessments are derived from the collation and calculation of diverse climate, topographical, and socioeconomic indicators, which are grouped under categories of exposure and adaptive capacity.

decrease in livestock and poultry health, and land availability for agriculture.[21] The indicator is then constructed based on the quartiles of this index. We next perform regressions including the interaction of our variable of interest and the indicator for high agricultural vulnerability. With the exception of column (1), coefficients on the interaction terms presented in Panel C of Table 5 are all positive and significant. The F-statistics that these results are jointly equal to zero indicate that we can reject the null hypothesis for the three sub-samples in columns (2) through (4). The total effect of an increase in the number of dry months for the most vulnerable women living in sub-districts in the highest quartile of the vulnerability index is 2.4 percentage points. These findings remain when we control for other climate vulnerability-associated variables, including those related to road/rail infrastructure and the fisheries sector.

4.4. Results focusing on agricultural households

We examine whether intra-family employment structure plays a role in shaping the climate-IPV relationship, with results presented in Table A3. We focus on households where the husband (who is also the household head in most cases) is employed in the agricultural sector. As seen in Panels A and B, there are statistically significant effects only for respondents in agricultural households, with more pronounced effects again for the lowest wealth quintile. Note that while results for the full sample in column (1) of the main results in Table 2 were not significant, the corresponding estimate in column (1) of Panel A in Table A3 which focuses on agricultural households, now is.

In Panels C and D, we delve deeper, focusing on samples by women's primary occupation and employment status. We find that the results are evident mostly for unemployed women in agricultural households. This finding lends support to the hypothesis that more dry periods largely

[21] For instance, for constructing the crop yield vulnerability index, the experts focused on four components of exposure: (1) consecutive dry days (2) riverine floods (3) flash floods (4) storm surge height.

impact women in relatively low-income households through the agricultural channel. These results are also consistent with our previous results pertaining to rural households whose livelihoods are likely tied to agricultural production.[22]

To complement our analysis on attitudes towards IPV, we use data from the DHS 2007 wave to estimate effects on the incidence of IPV for women employed directly in agriculture, assuming that deteriorating outside opportunities due to decreased agricultural income can increase IPV (Farmer and Tiefenthaler 1997).[23] We find some evidence that supports this in Table 6. Focusing on women employed in agriculture, there is a positive association between the frequency of dry months experienced over the past 3 years and the experience of IPV, especially sexual violence and the experience of both physical and sexual violence.[24] These additional findings lend support to the assertion that climatic variability reduces women's overall wellbeing.[25]

4.5. Other agency indicators

Until now, we have used women's perception of the acceptability of violent behavior to proxy for their status. In Table A4, we focus on the most vulnerable agricultural households and investigate whether dry shocks impact other aspects of women's agency. In Panel A, the analysis is limited to agricultural households (where either the respondent herself or her husband is engaged in agriculture), while Panel B focuses on women whose main occupation is agriculture. In column

[22] We considered evaluating changes in land use patterns but these are unlikely to be sizable given our three year focus.

[23] Using only one wave of data constrains statistical power because of reduced sample size as compared to the main analyses. In this case, we use region fixed effects only, while keeping the same set of controls as in equation (1). Perhaps as a consequence of the reduced sample size, considering impacts for unemployed women, or unemployed women with husbands employed in agriculture, yields mostly insignificant effects.

[24] Due to the restricted sample size, we are careful in interpreting these results.

[25] Abiona and Foureaux-Koppensteiner (2018) also find that droughts lead to an increase of domestic violence in Tanzania. In rural areas of the Peruvian Andes, Diaz and Saldarriaga (2023) report that a woman's experiences of IPV increases by 8.5 percentage points following dry shocks, with sexual IPV increasing by about 3 percentage points due to rainfall shocks during the cropping season. Epstein et al. (2020) similarly links negative rainfall shocks to higher IPV rates among adolescent girls and unemployed women. In contrast, Cools et al. (2020) found no strong evidence that droughts increase IPV.

(1), the dependent variable equals one if she does not participate in any of the four following decisions: her own healthcare, major household purchases, visits to her family or relatives, and child healthcare. In this case, the analysis uses data from the 2011 and 2014 DHS waves because of the uniformity in the question formulation and the response choices offered to participants in both periods. As a robustness check, in column (2), we use a decision-making index representing an average of her responses to the first three decision-related questions, using data from all three waves. Column (3) includes a "*freedom of movement*" binary dependent variable that equals one if she asserts having the freedom to visit the health center alone or with her children. In column (4), we measure financial independence with an indicator that equals one if a currently married woman who received cash earnings in the past 12 months makes joint decisions on how to use her earnings with her husband.[26]

Overall, the results support the hypothesis that a higher occurrence of dry months lowers women's agency. In both panels, an increase in the number of dry months increases the likelihood of women's exclusion from decision-making processes and decreases the probability of having control over her cash earnings. The estimates are somewhat higher in Panel B when we consider women employed in agriculture. For instance, an additional dry month increases the likelihood of not participating in decision-making by approximately 3.4 percentage points for married women in the lowest wealth quintile. These additional results further underline that climate shocks impact factors that influence women's agency.

5. Climate resilience investments shield women from IPV

---

[26] The BDHS has variation in the framing of certain questions and answers across the three waves. For instance, there was a change in the DHS 2017 wave pertaining to women's participation in decision-making, with changes in the list of options provided. The variable "*freedom of movement*" was not available in the DHS 2017, while new measures of empowerment were introduced. Given the smaller sample sizes, we employ district, survey-month, and survey-year fixed effects.

Starting in the 2000s, the Bangladeshi Government has been implementing several measures directly aimed at mitigating the effects of climate change. These initiatives were executed as a nationwide initiative to strengthen resilience, diminish vulnerability, and bolster adaptive capacities. In this section, we analyze the potential mitigating influences of these measures, focusing primarily on evaluating the efficacy of climate funds assigned to projects across regions of Bangladesh since 2010. We leverage the phased introduction of this Bangladesh Climate Change Trust (BCCT) initiative to evaluate its influence on the relationship between the frequency of dry shocks and IPV.

5.1. Bangladesh climate trust fund (BCCT) – Background

To support the Climate Change and Action Plan (BCCSAP), the Government of Bangladesh set up the Bangladesh Climate Change Trust (BCCT), first launched in 2008 and later revised in 2009.[27] The BCCT is a domestic climate change fund, and its creation symbolizes the government's proactive commitment to build climate resilience by addressing climate change implications via domestic resource mobilization. The trust fund has been functional since 2010 and works in collaboration with various entities such as NGOs, local ministries, public universities, and the private sector to implement climate resilience projects.

The variety of projects funded spans a broad spectrum, including infrastructure development, research, knowledge creation, promotion of renewable energy access, and livelihood preservation. It sets specific goals for addressing climate change mitigation, adaptation, and resilience, for example through the adoption of climate-tolerant technologies, biodiversity and environmental initiatives, and improving disaster response. The BCCT also aims to promote

[27] The BCCSAP encompasses six broad pillars: (1) Food security, social protection, and health; (2) comprehensive disaster management; (3) infrastructure; (4) research and knowledge management; (5) mitigation and low carbon development; (6) capacity building and institutional strengthening (MoEF, 2009).

sustainable development and execute projects focused on social empowerment and community-based human resource development. A number of these projects are women-centric, recognizing that climate change vulnerability places women at a higher risk due to entrenched gender disparities, societal norms, and unequal resource control.

5.2. Project allocation

We digitized the list of approved and finalized projects from the BCCT'S official site on the Bangladesh National Portal.[28] These files include information on project name, implementing agency, and the projected cost estimate for each initiative. Importantly, we also obtain details on the starting dates along with the originally scheduled and actual end dates for most projects. This information allows us to examine the possible attenuating impacts of these projects by evaluating proximity of survey respondents to ongoing projects. We are able to extract location data from the project title, supplementary documents on the portal, and from the Ministry of Environment, Forest, and Climate Change. This enables us to identify project locations at the *upazila* (sub-district) level, facilitating our analysis of the localized amelioration effects of these initiatives. In total, we pinpoint the sub-district locations of 183 projects spread throughout Bangladesh with varying start and ending dates spanning from 2010 and 2020.

Table A5 provides the summary statistics for socioeconomic, geographic, and climate-related vulnerability indices for *upazilas* with and without BCCT projects. The vulnerability of aid recipients is evident – on average, *upazilas* that received climate-related projects had relatively higher vulnerability indices pertaining to the number of people affected by natural disasters, resource availability for agriculture, fishery activities, and infrastructural properties like road and rail networks. Moreover, project recipients displayed a lower degree of economic development

[28] More information can be obtained here: http://www.bcct.gov.bd. Accessed on 13 January 2023.

and urbanization, are situated on lower grounds, are farther away from urban centers and roads, and closer to the coast, which is a significant factor. Yet despite these differences, there is an element of aid randomness noted in the literature.[29] Our empirical design takes these factors into account.

5.3. Methodology

Our objective is to quantify the extent to which these climate resilience projects shield women from the harmful IPV effects of climate shocks. We extend our strategy to assess possible mitigative effects using equation (3) below. The variable of interest is the interaction of the frequency of dry months and local climate-aid projects. More specifically:

$$y_{icdmt} = \beta numdrymths_{cdmt_{-36}} + \kappa BCCTproject_{sd(-)} + \pi(numdrymths_{cdmt_{-36}} \times BCCTproject_{sd(-)}) + \gamma \mathrm{W}_{\mathrm{cdmt}} + \theta \mathrm{X}_{\mathrm{icdmt}} + \alpha_d + \eta_m + \lambda_t + \omega_{dm} + \mu_{dt} + \epsilon_{icdt} \quad (3)$$

where $BCCTproject_{sd(-)}$ equals one when the respondent's cluster falls within a sub-district that had at least one BCCT project at the time the DHS survey was conducted. All other notation and variables remain consistent with those outlined in equations (1) and (2). The coefficient of interest is π, the additional effect of dry shocks for respondents in sub-districts with active BCCT projects.[30] Our expectation is that π will be negative, indicating that BCCT projects attenuates the impact of dry shocks on the outcome variable. We are also interested in the net effect of drought on acceptance of IPV in sub-districts with active BCCT projects, $\beta + \pi$. If this net effect is not

[29] Mujaffor (2019) clarifies that despite the BCCT's initial intention of utilizing domestic resources to protect areas susceptible to climate change, there exists a disparity in the allocation of funds, not necessarily reflecting the degree of vulnerability. Districts like Bagerhat, Khulna and Satkhira, significantly threatened by salinity and tidal surges, serve as examples. The fund allocation process, as it stands, appears to lack equitable focus, with the distribution of resources not consistently corresponding to the varying degrees of climate vulnerability. Rahman et al. (2016) reaches a similar conclusion.

[30] The methodology here is similar to Chatterjee and Merfeld (2021), which explores the shift in the relationship between shocks to agricultural productivity and infant sex ratio in India when households gain access to employment opportunities outside of the agricultural sector.

statistically different from zero, then that is empirical evidence that in the presence of BCCT projects, dry shocks no long cause increases in IPV acceptance for women.

To account for potential selection effects stemming from non-random project allocation, we follow Knutsen et al. (2017), Kotsadam et al. (2018), and Zhang and Huang (2023) by leveraging the location and time of which the BCCT projects are active.[31] Our empirical strategy involves comparing the effect for two groups of respondents: those residing in sub-districts in which at least one BCCT project had already been implemented at the time of the survey and those living in sub-districts that, at the time of the survey, had yet to implement a project. We augment equation (3) with an additional indicator variable $inactiveproject_{sd(+)}$ which equals one if a future BCCT project is planned in a particular sub-district but has not yet been implemented. As noted in the studies above, this strategy is essentially comparing between potentially selected sites where one has received the "treatment" (in that a project is functioning) while the other has not (a project is planned but is not functioning yet at the time of the survey). We also include the ($numdrymths_{cdmt_{-36}} \times inactiveproject_{sd(+)}$) interaction term. As discussed below, we also investigate treatment intensity by considering the number of both active and planned/inactive projects, as well as their interactions with our variable of interest.[32]

5.4. Results

The analysis begins by determining whether effects are attenuated by proximity to climate projects. We present the results in Table A6. We note that the estimated drought impacts, β in equation (3), align with the results in Table 2. However, the coefficients on the interaction terms

---

[31] Specifically, pre-existing gender norms and factors associated with such norms – including economic activity, urbanization, and access to infrastructure – could impact decisions regarding project location.

[32] In our dataset, it is possible to be in proximity to multiple active and inactive projects. The count of active projects varies from 0 to 11.

are measured with error except in the case of agriculture-dependent communities. Table 7 reports results for equation (3) when we focus on agriculture-dependent communities. Consistent with results in Table 5, β is positive and significant across all columns. The coefficient on the interaction term between drought and proximity to BCCT projects, π, is negative and measured precisely, indicating that the net effect of dry shocks diminishes considerably post BCCT project implementation. In column (2), we introduce an indicator for the presence of an inactive project (the variable $inactiveproject_{sd(+)}$ in equation 3) and an interaction term with dry shocks. There is little significance. We next explore how our effects vary based on the number of active projects in column (3). We find that being in close proximity to a higher number of active projects mitigates the influence of dry shocks by 1.5 percentage points for each additional aid project. This effect holds in column (4) when we condition on the number of inactive projects.

Table 8 examines the attenuation effects from the presence of climate projects by decomposing into three sub-samples based on wealth quintiles, as before. The results corroborate our previous results to illustrate that the relationship between dry shocks and women's tolerance of IPV changes markedly, especially amongst the poorest agricultural households. Importantly, across all the results presented in Tables 7 and 8, joint significance tests for $\beta + \pi = 0$ fail to reject the null. That is, the presence of BCCT projects moderates the impacts harmful consequences of dry shocks on women's acceptance of IPV.[33]

5.5. Robustness

We perform a number of robustness checks on the amelioration effects of BCCT projects. The first check pertains to the sample of respondents in our study. In this regard, we turn to the

[33] Although we anticipate partial attenuation of the main adverse impacts documented earlier, it is plausible to see stronger net effects of BCCT projects since they offer significant fallback options for women. Fetzer (2020), for instance, demonstrates that the link between monsoon rainfall and conflict in India virtually disappears after the workfare NREGA program was initiated.

most vulnerable respondents (in the lowest quintile) and use data on agricultural employment in Table A7. In column (1), we evaluate women whose primary occupation is in the agricultural sector. In column (2), we include women from households where either the respondent herself or her husband is engaged in agriculture. In column (3), we focus on women in the lowest quintile, who work in any sector, and whose spouses are employed in agriculture. Again, local BCCT projects moderate the negative effects of dry shocks across all columns in Table A7. The *p*-values on the joint tests $\beta + \pi = 0$ confirm this to be the case.

In Panel A of Table A8, we account for a number of pre-BCCT covariates at the sub-district level. More precisely, we include geographical factors like ground slope, elevation, proximity to the coast, and distance to the nearest road. Economic variables include nighttime luminosity, normalized difference vegetation index (NDVI), the sectoral composition of employment, and the proportion of the population within the working age bracket of 15 to 64 years. Measures of climate vulnerability include the number of people affected by natural disasters, a composite index for crop yield susceptibility, indicators for declines in livestock and poultry health, and a measure for the available agricultural land. Further, we include measures of vulnerability related to fish cultivation and harvest, road and rail infrastructure, as well as pre-BCCT levels of air pollution ($PM_{2.5}$). Across the three columns in Panel A of Table A8, the sign and significance of the interaction term between dry shocks and BCCT project remains unchanged.

So far, we have considered projects that were implemented before the survey date. This implies that our analysis includes projects that might have already ended. In Panel B of Table A8, we include only those projects that were active at the time of the survey (using the actual start and end dates of the project). In Panel C, we remove projects that were introduced most recently during the survey year, ensuring that we only consider those that have had some time to yield effects. These controls do not change the original results on the interaction terms.

Ideally, our analysis would incorporate all climate-aid projects since the establishment of the Fund. However, we are only able to obtain location data for a subset of projects, as noted above. Rustad et al. (2020) notes that the absence of data on other aid projects might mean that our control group has also received assistance at some point. This implies a conservative bias for us since this sort of contamination would mean that the coefficients we currently estimate are an underestimate. We also implemented a model using nearest-neighbor matching between women who lived in sub-districts with active BCCT projects versus those who did not, as presented in Table A9. The post-matching estimator is of the same sign but noisier, potentially because of the reduced sample size.[34]

5.6. The potential impact of other development assistance

5.6.1. Development assistance from other donors

Bangladesh has launched other development initiatives and in the absence of controlling for these, we might overstate the true attenuation afforded by BCCT projects.[35] Our data indicates that 27% of respondents residing in a sub-district with an ongoing BCCT project are also within 10 km of an active development aid project funded by other donors. In order to address this, we use a geocoded dataset released in 2016 by *AidData* to evaluate the localized effects of other aid projects funded by nine donors: USAID, JICA, World Bank, Asian Development Bank, EU, India,

[34] We implemented the nearest-neighbor match using individual characteristics primarily because of the possibility of migration. If the relatively more wealthy move away from vulnerable areas because they can afford to, which is likely true, then results based on climate vulnerability match characteristics for instance, may pick up only the relatively poor people who have no choice but to stay. In this case, post-matching estimator results are likely biased due to negative selection.

[35] Gallagher et al. (2023) notes that isolating the impact of cash grants post-disaster is complicated by the existence of several other federal disaster assistance programs.

UNDP, Islamic Development Bank, and DfID.[36] The dataset traces a total of 299 aid initiatives across 3,641 locations in Bangladesh from 2000 to 2015. Figure A1 illustrates the distribution of all projects throughout Bangladesh based on data from this source.

The dataset includes the actual start and end dates for several projects, providing scope to assess whether clusters were situated near aid projects prior to and/or after the survey.[37] Following Kotsadam et al. (2018), we limit our analysis to projects with precise geocodes (corresponding to precision coding 3 and below) and with information on when they were established and completed. With these restrictions, projects in 1,861 locations meet our criteria. We then code a variable that equals one if the respondent's cluster is within a 10 km radius of an ongoing development-assistance project at the time of the survey. We generate an interaction term between the number of dry months and this variable. The empirical design mirrors the main analysis (equation 3) except that we now include these new additional variables for aid from other sources.

The results are presented in Table A10. As in columns (1)-(3) of Panel A, the coefficients for the new interaction terms are negative. However, they are statistically significant only for the sample of three lowest wealth quintiles. This suggests a potential moderating effect from other assistance programs, which is expected. Panel B demonstrates that the attenuation impact of BCCT projects remains when we condition on other development projects that are within 10 km. We also note that on average, the magnitude of attenuation from other development projects are smaller than that of BCCT projects. This is suggestive evidence that BCCT projects better shield women from climate-related shocks as compared to general-purpose development projects.

[36] We use the "*Bangladesh Select Donors Geocoded Research Release, Version 1.1.1.*", released in April 2016. For further details, please see: *AidData. 2016. BangladeshSelectDonors_GeocodedResearchRelease_Level1_v1.1.1 geocoded dataset. Williamsburg, VA and Washington, DC: AidData. Accessed on [February 2023]. http://aiddata.org/research-datasets.*

[37] The aid projects span across several different sectors including agricultural development, power generation/renewable sources, education, health, food security, disaster prevention and preparedness, civilian peacebuilding, water supply and sanitation, amongst others.

5.6.2. Bangladesh climate change resilience fund

We also note the establishment of the Bangladesh Climate Change Resilience Fund (BCCRF) by the government in 2010, another climate resilience program simultaneously implemented during our study period.[38] The project was since closed in 2016 due to differences between donors, the World Bank, and the Bangladeshi government.[39] Relying on the official BCCRF annual reports prepared by the World Bank, we obtain information from 2011 through 2016. Table A11 provides details on each of the five investment projects under the BCCRF initiative, all of which started in 2012 and concluded in 2016. Although our robustness check in the preceding section accounts for the presence of some of these projects, we go further to code a variable that equals one if the sub-district is situated in a potentially BCCRF treated area from 2012 to 2016, zero otherwise. This variable equals zero in 2011. We then re-estimate our baseline model but exclude areas that benefited from multiple types of projects. Table A12, which is identified from variation in BCCT projects alone, shows that our results remain about the same.

5.6.3. Potential mechanisms

The increase in women's wellbeing near BCCT project sites may be prompted by the upswing in economic activities with subsequent impacts on IPV acceptance. In Table A13, we seek to evaluate how BCCT projects shape these relationships. By focusing on the sample of women in agriculture-dependent communities across different wealth strata, we present findings for outcomes that are related directly to women's agency through improved access to information, enhanced financial opportunities, increased welfare, and greater awareness. This is accomplished by estimating

[38] The BCCRF is owned and managed by the Ministry of Environment and Forests, with a governance structure that includes a Government Council and a Management Committee. The World Bank monitors the transparency and accountability of the BCCRF's operations.

[39] Source: The Guardian (2016): *Climate finance dispute prompts Bangladesh to return £13m of UK aid*; https://www.theguardian.com/global-development/2016/nov/10/climate-finance-dispute-bangladesh-returns-13-million-uk-aid-world-bank; Accessed 8/29/2023.

regressions models of selected outcomes on an indicator for the presence of an ongoing BCCT project while conditioning on the presence of other ongoing development projects. As seen in columns (1)-(4), active BCCT projects play significant roles in enhancing access to media, in earning cash, and in utilizing transport facilities such as bicycles, motorcycles or cars. For instance, as seen in column (1), a woman residing in a sub-district with an ongoing BCCT project has a 3.4 percent higher likelihood of accessing any form of media, and has a 3% and 4.4% increased change of using some form of transportation and of reporting cash earnings, respectively. These effects are generally more pronounced among the most vulnerable in the lowest wealth quintile. Taken together, these results are suggestive that initiatives promoting climate resilience have effects on factors that may improve women's agency.

5.7. Discussion

The evidence generated in this section aligns with the literature that analyzes heterogeneity in the effects of environmental shocks and assesses how policies may alleviate impacts (Barreca et al. 2016, Cohen and Dechezleprêtre 2017, Fetzer 2020, Gallagher et al. 2023, and Kelly and Molina 2023). For instance, Ajefu and Abiona (2020) find that land tenure security fully cushions the detrimental effects of extreme droughts for agricultural dependent households in Malawi. Sarma (2022), investigating NREGA's influence on moderating the impact of income shocks on domestic violence, reveals that the adverse effects of dry shocks on domestic violence are considerably attenuated by the program's implementation. Rustad et al. (2020) finds that children exposed to drought who lived closer to a development aid project site are less likely to develop undernutrition in Sub-Saharan Africa.

Our results underline the importance of social safety nets for vulnerable agricultural communities experiencing climate change. While our evidence reveals the link between BCCT projects and increased economic activities, additional research could shed more light on the externalities generated by climate projects that enable household to undertake adaptive investments to lessen income risks which, in turn, facilitates women's social protection. Further, our finding that BCCT projects have relatively more powerful moderating influences than other types of development assistance suggests a need for a closer assessment of aid effectiveness.

6. Conclusion

This paper empirically documents how climate-induced weather shocks can generate detrimental social spillovers along existing social, economic, and cultural inequalities in developing countries. We employ geo-referenced data on weather merged with individual-level information from four waves of the BDHS to analyze how weather variability affects women's tolerance of violence. Our baseline strategy, consistent with the relevant literature, leverages variation in the cumulative number of months, over the past 3 years prior to survey, during which rainfall realization was at least one standard deviation below the long-term average, while also controlling for other weather measures, individual and household level controls, district-specific seasonality, and local trends. The use of controls for other weather variables while evaluating the effect of dry shocks is unique to our study and important since factors such as temperature and rainfall tend to be correlated and considering these in isolation can lead to erroneous inference.

Our results indicate that an increase in the frequency of dry months leads to a sizeable increase in among poor women and women living in agriculture-dependent areas. We find no effects on wet or hot months. Heterogeneity analyses reveal that these effects are more pronounced for women residing in rural areas, those who are illiterate, and those living in less developed sub-districts. Our analyses also demonstrate that the incidence of dry shocks is associated with women's exclusion from household decision-making and lack of control over earnings.

Our study also examines the moderating effects of a specific local climate-resilience initiative – the Bangladesh Climate Change Trust (BCCT). We find that the implementation of BCCT projects in communities reliant on agriculture eliminates the adverse impact of dry shocks on women's likelihood of accepting IPV. Additionally, these projects demonstrate positive contributions in improving multiple aspects of women's wellbeing. We conduct various sensitivity analyses and control for potential confounding factors to underline the robustness of these results.

Taken together, our research contributes to the literature by providing a comprehensive assessment of changing climate and women's agency in Bangladesh. We add further evidence that the poorest women in the most vulnerable contexts are bearing the brunt of climate change; however, we also highlight the positive spillover effects of targeted resilience policies in protecting such women. Our study underscores the urgent need for policy interventions that address the intersecting challenges of climate change, gender inequality and socio-economic disadvantage.

References

Abiona, O. and Koppensteiner, M.F., 2018. The impact of household shocks on domestic violence: Evidence from Tanzania. IZA DP No. 11992.

Adhvaryu, A., Kala, N. and Nyshadham, A., 2020. The light and the heat: Productivity co-benefits of energy-saving technology. *Review of Economics and Statistics*, *102*(4), pp.779-792.

Afridi, F., Mahajan, K. and Sangwan, N., 2022. The gendered effects of droughts: Production shocks and labor response in agriculture. *Labour Economics*, *78*, p.102227.

Ajefu, J.B. and Abiona, O., 2020. The mitigating impact of land tenure security on drought-induced food insecurity: evidence from rural Malawi. *The Journal of Development Studies*, *56*(12), pp.2169-2193.

Amin, M.R., Zhang, J. and Yang, M., 2014. Effects of climate change on the yield and cropping area of major food crops: A case of Bangladesh. *Sustainability*, *7*(1), pp.898-915.

Aragón, Fernando M., Francisco Oteiza, and Juan Pablo Rud. 2021. "Climate Change and Agriculture: Subsistence Farmers' Response to Extreme Heat." *American Economic Journal: Economic Policy* 13 (1): 1–35.

Banerjee, R. and Maharaj, R., 2020. Heat, infant mortality, and adaptation: Evidence from India. *Journal of Development Economics*, *143*, p.102378.

Bangladesh Bureau of Statistics, 2016. Report on violence against women (VAW) survey 2015.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M. and Shapiro, J.S., 2016. Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, *124*(1), pp.105-159.

Baskerville, G.L. and Emin, P., 1969. Rapid estimation of heat accumulation from maximum and minimum temperatures. *Ecology*, *50*(3), pp.514-517.

Bengesai, A.V. and Khan, H.T., 2023. Exploring the association between attitudes towards wife beating and intimate partner violence using a dyadic approach in three sub-Saharan African countries. *BMJ open*, *13*(6), p.e062977.

Blom, S., Ortiz-Bobea, A. and Hoddinott, J., 2022. Heat exposure and child nutrition: Evidence from West Africa. *Journal of Environmental Economics and Management*, *115*, p.102698.

Burgess, R., Deschenes, O., Donaldson, D. and Greenstone, M., 2014. The unequal effects of weather and climate change: Evidence from mortality in India. *Cambridge, United States: Massachusetts Institute of Technology, Department of Economics. Manuscript*.

Burgess, R., Deschenes, O., Donaldson, D. and Greenstone, M., 2017. Weather, climate change and death in India. *University of Chicago*.

Burke, M., Hsiang, S.M. and Miguel, E., 2015. Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), pp.235-239.

Chatterjee, J. and Merfeld, J.D., 2021. Protecting girls from droughts with social safety nets. *World Development*, *147*, p.105624.

Cohen, F. and Dechezleprêtre, A., 2017. Mortality inequality, temperature and public health provision: evidence from Mexico. *Grantham Research Institute on Climate Change and the Environment Working Paper*, *268*.

Colmer, J. and Doleac, J. 2023. Access to Guns in the Heat of the Moment: More Restrictive Gun Laws Mitigate the Effect of Temperature on Violence. CESifo Working Paper No. 10525.

Cools, S., Flatø, M. and Kotsadam, A., 2020. Rainfall shocks and intimate partner violence in sub-Saharan Africa. *Journal of peace research*, *57*(3), pp.377-390.

Country Climate and Development Report for Bangladesh, World Bank Report, 2022

Dasgupta, A., 2017. Can the major public works policy buffer negative shocks in early childhood? Evidence from Andhra Pradesh, India. *Economic Development and Cultural Change*, *65*(4), pp.767-804.

Dell, M., Jones, B.F. and Olken, B.A., 2012. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), pp.66-95.

Dell, M., Jones, B.F. and Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. *Journal of Economic literature*, *52*(3), pp.740-798.

Deschenes, 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), pp.152-185.

Díaz, J.J. and Saldarriaga, V., 2023. A drop of love? Rainfall shocks and spousal abuse: evidence from rural Peru. *Journal of health economics*, *89*, p.102739.

Epstein, A., Bendavid, E., Nash, D., Charlebois, E.D. and Weiser, S.D., 2020. Drought and intimate partner violence towards women in 19 countries in sub-Saharan Africa during 2011-2018: A population-based study. *PLoS Medicine*, *17*(3), p.e1003064.

Farmer, A. and Tiefenthaler, J., 1997. An economic analysis of domestic violence. *Review of social Economy*, *55*(3), pp.337-358.

Fetzer, T., 2020. Can workfare programs moderate conflict? Evidence from India. *Journal of the European Economic Association*, *18*(6), pp.3337-3375.

Gallagher, J., Hartley, D. and Rohlin, S., 2023. Weathering an unexpected financial shock: the role of federal disaster assistance on household finance and business survival. *Journal of the Association of Environmental and Resource Economists*, *10*(2), pp.525-567.

Garg, T., Jagnani, M. and Taraz, V., 2020. Temperature and human capital in India. *Journal of the Association of Environmental and Resource Economists*, *7*(6), pp.1113-1150.

Geruso, M. and Spears, D., 2018. *Heat, humidity, and infant mortality in the developing world* (No. w24870). National Bureau of Economic Research.

Guimbeau, A., Ji, X.J., Menon, N. and van der Meulen Rodgers, Y., 2023. Mining and women's agency: Evidence on acceptance of domestic violence and shared decision-making in India. *World development*, *162*, p.106135.

Guiteras, R., 2009. The impact of climate change on Indian agriculture. *Manuscript, Department of Economics, University of Maryland, College Park, Maryland*, pp.1-54.

Hanifi, S.M.A., Menon, N. and Quisumbing, A., 2022. The impact of climate change on children's nutritional status in coastal Bangladesh. *Social Science & Medicine*, *294*, p.114704.

Hasan, M.M. and Chongbo, W., 2020. Estimating energy-related CO2 emission growth in Bangladesh: The LMDI decomposition method approach. *Energy Strategy Reviews*, *32*, p.100565.

Henderson, J.V., Storeygard, A. and Weil, D.N., 2012. Measuring economic growth from outer space. *American economic review*, *102*(2), pp.994-1028.

Hsiang, S.M., Burke, M. and Miguel, E., 2013. Quantifying the influence of climate on human conflict. *Science*, *341*(6151), p.1235367.

Ibánez, A.M., Romero, J. and Velásquez, A., 2021. Temperature Shocks, Labor Markets and Migratory Decisions in El Salvador. *Unpublished paper. World Bank, Washington, DC.*

Isen, A., Rossin-Slater, M. and Walker, R., 2017. Relationship between season of birth, temperature exposure, and later life wellbeing. *Proceedings of the National Academy of Sciences*, *114*(51), pp.13447-13452.

Iyer, L. and Topalova, P.B., 2014. Poverty and crime: evidence from rainfall and trade shocks in India. *Harvard Business School BGIE Unit Working Paper*, (14-067).

Kelly, D. and Molina, R., 2023. Adaptation Infrastructure and its Effects on Property Values in the Face of Climate Risk. Forthcoming at the *Journal of the Association of Environmental and Resource Economists.*

Kishor, S., 2005. Domestic violence measurement in the demographic and health surveys: The history and the challenges. *Division for the Advancement of Women*, *2005*, p.1.

Knutsen, C.H., Kotsadam, A., Olsen, E.H. and Wig, T., 2017. Mining and local corruption in Africa. *American Journal of Political Science*, *61*(2), pp.320-334.

Kotsadam, A., Østby, G., Rustad, S.A., Tollefsen, A.F. and Urdal, H., 2018. Development aid and infant mortality. Micro-level evidence from Nigeria. *World Development*, *105*, pp.59-69.

La Mattina, G., 2013. Armed conflict and domestic violence: Evidence from Rwanda. *SSRN Electronic Journal*, *10*.

Lee, J., 2016. Climate variability influences women's attitudes towards intimate partner violence (IPV). Master's Theses.

Liu, M., Shamdasani, Y. and Taraz, V., 2023. Climate change and labor reallocation: Evidence from six decades of the Indian Census. *American Economic Journal: Economic Policy*, *15*(2), pp.395-423.

Maconga, Carson W. 2023. "Arid Fields Where Conflict Grows: How Drought Drives Extremist Violence in Sub-Saharan Africa." *World Development Perspectives* 29: 100472.

Maccini, S. and Yang, D., 2009. Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, *99*(3), pp.1006-1026.

Macours, K., Premand, P. and Vakis, R., 2022. Transfers, Diversification and Household Risk Strategies: Can productive safety nets help households manage climatic variability? *The Economic Journal*, *132*(647), pp.2438-2470.

Mendelsohn, R., Nordhaus, W.D. and Shaw, D., 1994. The impact of global warming on agriculture: a Ricardian analysis. *The American economic review*, pp.753-771.

Ministry of Environment and Forests (MoEF), Bangladesh Climate Change Strategy and Action Plan 2009. Government of the People's Republic of Bangladesh, Dhaka, Bangladesh. Xviii + 76pp.

Mujaffor, S.A., 2019. Bangladesh Climate Change Trust Fund Policy: Challenges and Way Forward. *Bangladesh Journal of Administration and Management*, *32*(2), pp.42-59.

Mullins, J.T. and White, C., 2020. Can access to health care mitigate the effects of temperature on mortality? *Journal of Public Economics*, *191*, p.104259.

National Institute of Population Research and Training (NIPORT), Mitra and Associates and ICF International. 2013. *Bangladesh Demographic and Health Survey 2011*. Dhaka, Bangladesh and Calverton, Maryland, USA: NIPORT, Mitra and Associates, and ICF International.

Nguyen, C.V., Nguyen, M.H. and Nguyen, T.T., 2022. *Climate change, cold waves, heat waves, and mortality: Evidence from a lower middle-income country* (No. 1034). GLO Discussion Paper.

Pople, A., Hill, R., Dercon, S. and Brunckhorst, B., 2023. Anticipatory cash transfers in climate disaster response. Working paper.

Rahman, M.A., Kang, S., Nagabhatla, N. and Macnee, R., 2017. Impacts of temperature and rainfall variation on rice productivity in major ecosystems of Bangladesh. *Agriculture & Food Security*, *6*, pp.1-11.

Rahman, S.M., Ahmad, M.M. and Alam, M.S., 2016. From strategy to execution: the case of local climate fund in Bangladesh. *International Journal of Environmental Policy and Decision Making*, *2*(1), pp.1-18.

Randazzo, T., Pavanello, F. and De Cian, E., 2023. Adaptation to climate change: Air-conditioning and the role of remittances. *Journal of Environmental Economics and Management*, *120*, p.102818.

Rustad, S.A., Rosvold, E.L. and Buhaug, H., 2020. Development aid, drought, and coping capacity. *The Journal of Development Studies*, *56*(8), pp.1578-1593.

Sarma, N., 2022. Domestic violence and workfare: An evaluation of India's MGNREGS. *World Development*, *149*, p.105688.

Sarsons, H., 2015. Rainfall and conflict: A cautionary tale. *Journal of development Economics*, *115*, pp.62-72.

Schneider, D., Harknett, K. and McLanahan, S., 2016. Intimate partner violence in the great recession. *Demography*, *53*(2), pp.471-505.

Sekhri, S. and Hossain, M.A., 2023. Water in scarcity, women in peril. Forthcoming at the *Journal of the Association of Environmental and Resource Economists.*

Sekhri, S. and Storeygard, A., 2014. Dowry deaths: Response to weather variability in India. *Journal of development economics*, *111*, pp.212-223.

Shah, M. and Steinberg, B.M., 2017. Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy*, *125*(2), pp.527-561.

Snyder, R.L., 1985. Hand calculating degree days. *Agricultural and forest meteorology*, *35*(1-4), pp.353-358.

Titilayo, A., Omisakin, O.A. and Ehindero, S.A., 2014. Influence of women's attitude on the perpetration of gender-based domestic violence in Nigeria. *Gender and Behaviour*, *12*(2), pp.6420-6429.

Tsaneva, M., 2020. The effect of weather variability on child marriage in Bangladesh. *Journal of International Development*, *32*(8), pp.1346-1359.

Ubilava, D., Hastings, J. and Atalay, K. 2022. Agricultural Windfalls and Seasonality of Political Violence in Africa. *American Journal of Agricultural Economics*, forthcoming.

Uthman, O.A., Moradi, T. and Lawoko, S., 2011. Are individual and community acceptance and witnessing of intimate partner violence related to its occurrence? Multilevel structural equation model. *PloS one*, *6*(12), p.e27738.

Zhang, C. and Huang, Z., 2023. Foreign Aid, Norm Diffusion, and Local Support for Gender Equality: Comparing Evidence from the World Bank and China's Aid Projects in Africa. *Studies in Comparative International Development*, pp.1-32.

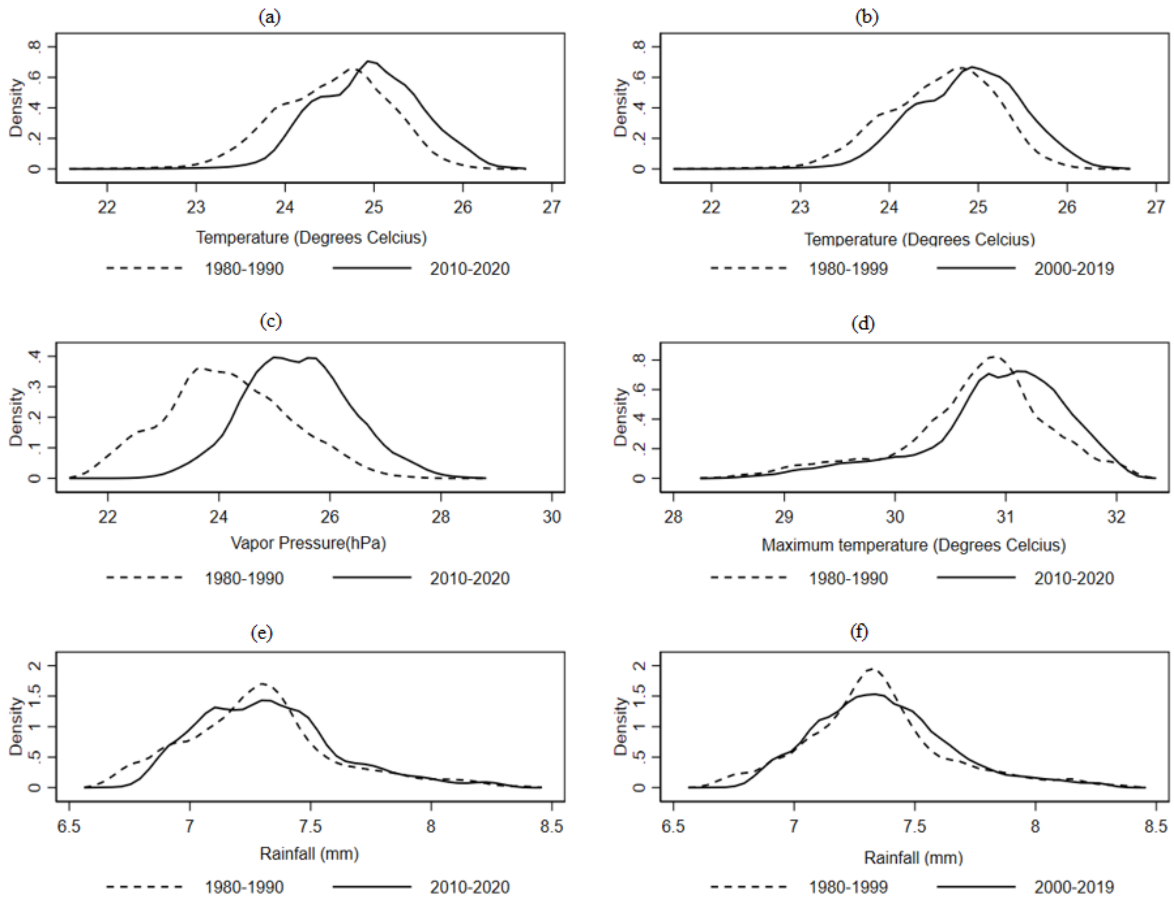
Zhang, P., Deschenes, O., Meng, K. and Zhang, J., 2018. Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, *88*, pp.1-17.

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*, pp.8-31.

Figure 1: Location of BDHS clusters

Notes: Figure 1 shows the location of all BDHS clusters in our sample for 2007 (on the left), and for 2011, 2014 and 2017 (on the right).

Figure 2: Kernel densities of temperature, rainfall, and vapor pressure, 1980-2020



Notes: Author's calculations using the Copernicus Climate Change Service for different periods. The observations are calculated at the DHS cluster-year level. We use the location of clusters in the BDHS 2007, 2011, 2014, and 2017, and match the gridded climate data to the cluster level using the IDW method as explained in the text. Temperature and vapor pressure are annual averages calculated using monthly values. Precipitation is calculated as the sum of monsoon rainfall, in logs (using monthly values for precipitation for the months of June through October only). Maximum temperature is the annual average calculated using monthly values for the monsoon period. The short-dash black line denotes the first period distribution (1980-1990 or 1980-1999), and the solid black line represents that distribution for the last period considered (2010-2020 or 2000-2019).

Table 1: Summary statistics of selected variables

	Mean	Standard Deviation
Panel A: Empowerment indicators		
Attitudes towards DV (=1 if agrees with at least one reason)	0.268	0.443
Participates in no decision	0.168	0.374
Decision index	0.671	0.392
Freedom of movement	0.670	0.470
Control over own earnings	0.576	0.494
Panel B: Experience of domestic violence (DHS 2007 only)		
Physical	0.190	0.392
Sexual	0.107	0.309
Physical and/or sexual	0.240	0.427
Physical and sexual	0.057	0.231
Panel C: Weather-related variables		
Number of dry months	5.670	2.495
Number of wet months	4.420	1.734
Panel D: Women and household characteristics		
Respondent's current age	31.193	9.030
Husband's age	40.091	11.133
Rural (=1 if in rural area)	0.723	0.448
Women's education:		
Primary	0.307	0.461
Secondary	0.374	0.484
Tertiary	0.093	0.291
Husband's education:		
Primary	0.297	0.457
Secondary	0.288	0.453
Tertiary	0.142	0.349
Religion (=1 if Muslim)	0.901	0.299
Age at first cohabitation	15.788	2.855
Number of children (<age 5)	0.677	0.790

Notes: the data sources include the BDHS 2011, 2014, and 2017 in Panels A and D. The data used in Panel B is only from the 2007 BDHS wave. We present the summary statistics for the full sample of respondents. The source of data for the weather variables is the Copernicus Climate Change Service.

Table 2: The effects of climate shocks on women's attitudes towards IPV

	Dependent Variable: Justifies IPV for at least one reason					
	Sample restricted to:					
	All	Agriculture-Dependent Communities	Non Agriculture-Dependent Communities	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Number of dry months (past 3 years)	0.005	0.010**	-0.008	0.009**	0.011**	0.016**
(below 1 SD of historical average rainfall)	(0.004)	(0.005)	(0.008)	(0.004)	(0.005)	(0.007)
Number of wet months (past 3 years)	-0.003	-0.001	0.003	-0.006	-0.004	0.000
(above 1 SD of historical average rainfall)	(0.004)	(0.005)	(0.011)	(0.005)	(0.006)	(0.008)
Number of hot months (past 3 years)	-0.003	-0.004	-0.003	-0.004	-0.005	-0.006
(above 1 SD of historical average temperature)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)
Observations	47,885	23,108	22,608	27,085	17,703	8,657
R-squared	0.110	0.118	0.120	0.112	0.131	0.156
Individual and household controls	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓	✓
Month, year of survey FE	✓	✓	✓	✓	✓	✓
District x Month of survey FE	✓	✓	✓	✓	✓	✓
District x Year of survey FE	✓	✓	✓	✓	✓	✓

Notes: The table shows the coefficients of the variables for climate shocks. The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. Column (1) reports full sample results. Columns (2) and (3) report results from subsamples for agricultural-dependent and non-agricultural-dependent communities. Columns (4), (5) and (6) report results from subsamples for the three poorest, two poorest, and the poorest quantiles. In all columns, we report the coefficients on the variable of interest which is the number of months in which the rainfall realization was below the historical average rainfall (from 1980-2000) by at least one standard deviation, over three years prior to the survey year. The controls include the respondent's age, the husband's age, a rural dummy, three indicator variables for the woman's highest level of educational attainment (with the excluded category being "no education at all"), similar indicators for the husband's level of educational attainment, age at first marriage, a dummy variable for religion, and a continuous variable for the number of living children (below the age of 5) in the household. The controls for climatic conditions at the time of the survey are the number of wet months and the number of hot months 36 months prior to survey date, temperature bins, rain, and rain squared, as explained in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table 3: Climate shocks and attitudes towards IPV: Heterogeneous effects

	Dependent Variable: Justifies IPV for at least one reason					
	Sample restricted to: lowest quintile					
	Residence		Literacy		Prosperity	
	Rural	Urban	Literate	Illiterate	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Number of dry months (past 3 years)	0.019**	-0.011	0.016	0.018**	0.013	0.022***
(below 1 SD of historical average rainfall)	(0.008)	(0.032)	(0.012)	(0.008)	(0.014)	(0.008)
Number of wet months (past 3 years)	-0.002	-0.026	0.006	-0.004	-0.002	0.002
(above 1 SD of historical average rainfall)	(0.008)	(0.033)	(0.010)	(0.011)	(0.011)	(0.012)
Number of hot months (past 3 years)	-0.004	0.016	-0.006	-0.009	-0.006	-0.005
(above 1 SD of historical average temperature)	(0.006)	(0.036)	(0.008)	(0.008)	(0.014)	(0.008)
Observations	7,316	1,308	3,958	4,677	4,337	4,309
R-squared	0.160	0.281	0.205	0.181	0.171	0.159
Individual and household controls	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓	✓
Month, year of survey FE	✓	✓	✓	✓	✓	✓
District x Month of survey FE	✓	✓	✓	✓	✓	✓
District x Year of survey FE	✓	✓	✓	✓	✓	✓

Notes: The table shows the coefficients on the variables for climate shocks. The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table 4: The effects of climate shocks, by cohort, on women's attitudes towards IPV

	Dependent Variable: Justifies IPV for at least one reason Sample restricted to:					
	All	Agriculture Dependent Communities	Non Agriculture Dependent Communities	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Number of dry months (past 3 years)	0.001	0.005	-0.009	-0.015	-0.031	-0.068**
(below 1 SD of historical average rainfall)	(0.014)	(0.019)	(0.022)	(0.018)	(0.020)	(0.031)
No. of dry months x birth cohort 1960s	0.002	-0.001	0.005	0.022	0.033	0.080**
	(0.014)	(0.020)	(0.021)	(0.018)	(0.020)	(0.031)
No. of dry months x birth cohort 1970s	0.005	0.006	0.001	0.022	0.041**	0.077**
	(0.013)	(0.019)	(0.021)	(0.017)	(0.020)	(0.030)
No. of dry months x birth cohort 1980s	0.005	0.004	0.003	0.024	0.044**	0.093***
	(0.013)	(0.019)	(0.021)	(0.017)	(0.020)	(0.030)
No. of dry months x birth cohort 1990s	0.004	0.006	-0.001	0.026	0.046**	0.082***
	(0.013)	(0.019)	(0.020)	(0.017)	(0.020)	(0.030)
Total effect for birth cohort 1960s	0.003	0.005	-0.005	0.008	0.002	0.012
p-value	[0.615]	[0.469]	[0.626]	[0.203]	[0.732]	[0.225]
Total effect for birth cohort 1970s	0.006	0.011**	-0.009	0.006	0.010	0.009
p-value	[0.233]	[0.036]	[0.311]	[0.171]	[0.100]	[0.252]
Total effect for birth cohort 1980s	0.005	0.009*	-0.007	0.010**	0.013**	0.025***
p-value	[0.233]	[0.076]	[0.440]	[0.043]	[0.020]	[0.002]
Total effect for birth cohort 1990s	0.004	0.012**	-0.010	0.011**	0.015**	0.015
p-value	[0.350]	[0.043]	[0.236]	[0.025]	[0.019]	[0.113]
Observations	27,085	17,703	8,657	27,085	17,703	8,657
R-squared	0.113	0.132	0.159	0.113	0.132	0.159
Cohort FE	✓	✓	✓	✓	✓	✓
Number of wet months x cohort	✓	✓	✓	✓	✓	✓
Number of hot months x cohort	✓	✓	✓	✓	✓	✓

Notes: The table shows the coefficients for the interactions between the number of dry months and indicator variables for each cohort. Column (1) reports full sample results. Columns (2) and (3) report results from subsamples for agricultural-dependent and non-agricultural-dependent communities. Columns (4), (5) and (6) report results from subsamples for the three poorest, two poorest, and the poorest quantiles. The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. *p*-values in square brackets. ***p<0.01, **p<0.05, *p<0.1.

Table 5: The heterogeneous effects of climate shocks in agriculture

	Dependent Variable: Justifies IPV for at least one reason			
	Sample restricted to:			
	All	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)
Panel A: Sample restricted to >= median employment share in agriculture				
Number of dry months (past 3 years)	0.010**	0.010*	0.014**	0.031***
(below 1 SD of historical average rainfall)	(0.005)	(0.005)	(0.007)	(0.010)
Observations	23,108	12,971	8,521	4,165
R-squared	0.118	0.116	0.132	0.164
Panel B: Sample restricted to < median employment share in agriculture				
Number of dry months (past 3 years)	-0.008	0.005	0.007	0.010
(below 1 SD of historical average rainfall)	(0.008)	(0.010)	(0.011)	(0.013)
Observations	22,608	12,966	8,444	4,132
R-squared	0.120	0.133	0.165	0.195
Panel C: Considering climate vulnerability indices				
Number of dry months (past 3 years)	0.004	0.007	0.009	0.013*
(below 1 SD of historical average rainfall)	(0.004)	(0.005)	(0.006)	(0.008)
Agricultural vulnerability index (upper quartile)	-0.010	-0.056**	-0.051	-0.054
	(0.024)	(0.028)	(0.032)	(0.041)
Number of dry months x agricultural vul. index	0.004	0.008*	0.008*	0.011*
	(0.003)	(0.004)	(0.005)	(0.006)
Total effect for upper quartile vulnerability	0.008	0.015	0.017	0.024
F-statistic	2.25	8.12	7.20	8.60
p-value	[0.134]	[0.004]	[0.007]	[0.003]
Observations	47,885	27,085	17,703	8,657
R-squared	0.111	0.113	0.131	0.157

Notes: The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. *p*-values in square brackets. ***p<0.01, **p<0.05, *p<0.1.

Table 6: The effect of climate shocks on the experience of IPV

	Sample restricted to: women employed in agriculture			
	Form of domestic violence:			
	physical	sexual	either physical or sexual	both physical and sexual
	(1)	(2)	(3)	(4)
Number of dry months (past 3 years)	0.004	0.033***	0.021	0.015*
(below 1 SD of historical average rainfall)	(0.013)	(0.012)	(0.018)	(0.008)
Number of wet months (past 3 years)	0.020	-0.017	-0.001	0.005
(above 1 SD of historical average rainfall)	(0.016)	(0.013)	(0.018)	(0.010)
Number of hot months (past 3 years)	-0.028**	0.014	-0.014	0.000
(above 1 SD of historical average temperature)	(0.014)	(0.011)	(0.015)	(0.009)
Observations	589	589	589	589
R-squared	0.104	0.113	0.145	0.080

Notes: The table shows the coefficients of the variables for climate shocks. We use data from the DHS 2007 wave only. The dependent variables relate to the experience of domestic violence during the year prior to the survey. We consider the sample of women whose main occupation was in the agricultural sector. All regressions include the same controls used in the main analysis. Region fixed effects are included. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table 7: Climate shocks, attitudes towards IPV and BCCT projects

Dependent Variable: Justifies IPV for at least one reason				
	Sample restricted to: Respondents in agriculture-dependent communities			
	(1)	(2)	(3)	(4)
Number of dry months (past 3 years)	0.011**	0.010**	0.011**	0.010*
(below 1 SD of historical average rainfall)	(0.005)	(0.005)	(0.005)	(0.005)
BCCT project (active before survey)	0.062*	0.061*		
	(0.036)	(0.036)		
Number of dry months x BCCT project	-0.018**	-0.018**		
	(0.008)	(0.008)		
Inactive BCCT project (active after survey)		-0.011		
		(0.037)		
Number of dry months x inactive BCCT project		0.002		
		(0.005)		
Number of BCCT projects			0.050*	0.048
			(0.030)	(0.030)
Number of dry months x num of BCCT projects			-0.015**	-0.015**
			(0.007)	(0.007)
Number of inactive BCCT projects				-0.024
				(0.026)
Number of dry months x num of inactive projects				0.002
				(0.004)
Joint test:				
num. of dry months + (num. of dry months x BCCT) = 0	-0.007	0.008	-0.005	-0.005
F-statistic	0.84	0.92	0.42	0.54
p-value	[0.360]	[0.337]	[0.516]	[0.540]
Observations	23,108	23,108	23,108	23,108
R-squared	0.118	0.118	0.118	0.118

Notes: The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. *BCCT project* is a dummy variable that equals to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted. *Inactive BCCT project* is a dummy variable that equals one if there is a known future BCCT project in a sub-district, but that had not yet been established at the time of the survey. '*num of BCCT projects*' is the number of BCCT projects implemented before the survey and '*num of inactive projects*' is the number of projects that will be implemented after the survey year in a particular sub-district. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. *p*-values in square brackets. ***p<0.01, **p<0.05, *p<0.1.

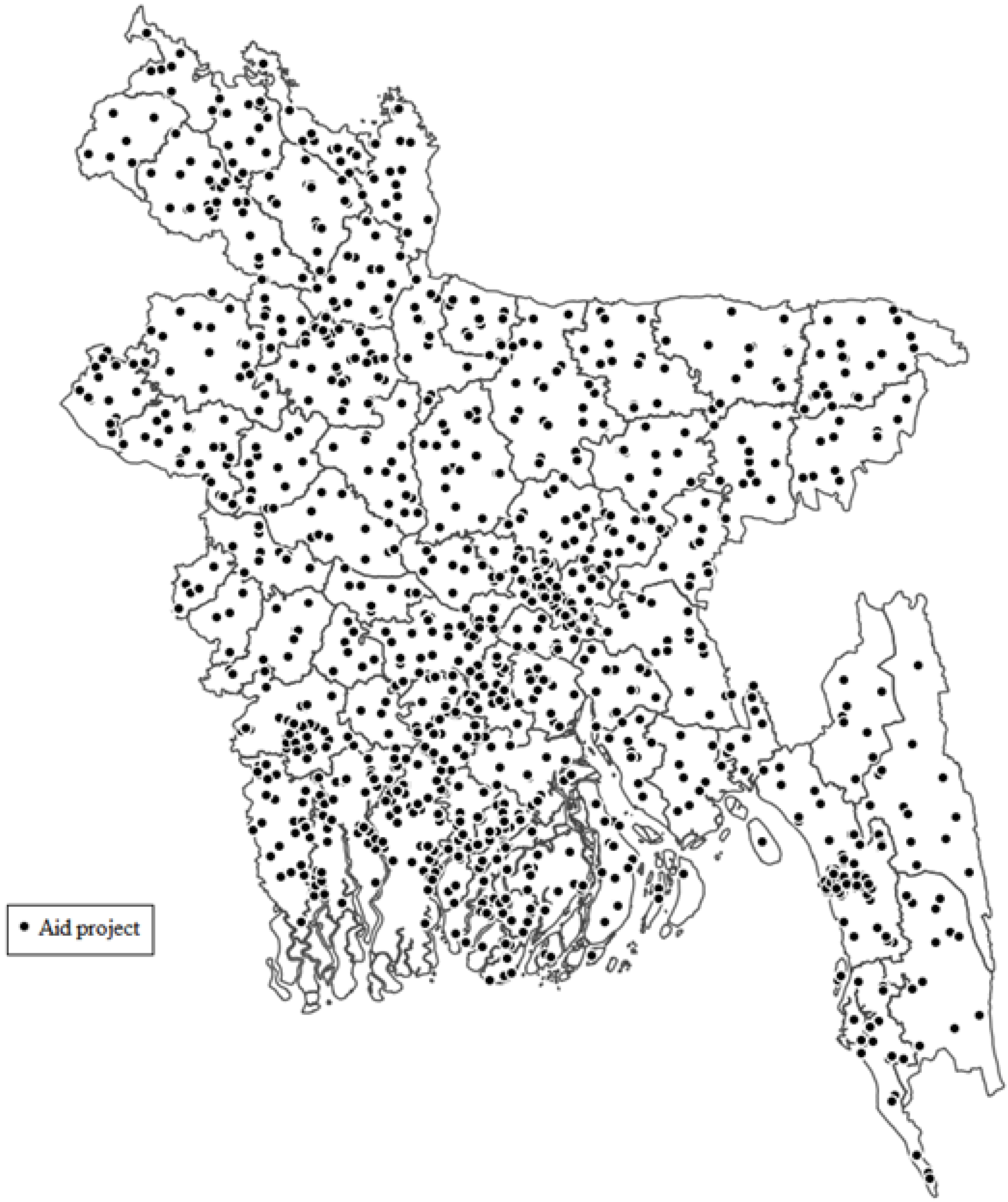
Table 8: Climate shocks, attitudes towards IPV and BCCT projects

	Dependent Variable: Justifies IPV for at least one reason							
	Sample restricted to: Respondents in agriculture-dependent communities							
	All	Three lowest quintiles	Two lowest quintiles	Lowest quintile	All	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of dry months (past 3 years)	0.011**	0.010*	0.011*	0.022***	0.010**	0.009*	0.010	0.020**
(below 1 SD of historical average rainfall)	(0.005)	(0.005)	(0.006)	(0.008)	(0.005)	(0.005)	(0.006)	(0.008)
BCCT project (active before survey)	0.062*	0.077*	0.038	0.080	0.061*	0.075*	0.037	0.076
	(0.036)	(0.040)	(0.046)	(0.074)	(0.036)	(0.040)	(0.046)	(0.074)
Number of dry months x BCCT project	-0.018**	-0.020**	-0.020**	-0.035**	-0.018**	-0.020**	-0.020**	-0.035**
	(0.008)	(0.008)	(0.010)	(0.014)	(0.008)	(0.008)	(0.010)	(0.014)
Inactive BCCT project (active after survey)					-0.011	-0.034	-0.034	-0.094*
					(0.037)	(0.041)	(0.048)	(0.055)
Number of dry months x inactive BCCT project					0.002	0.005	0.005	0.012
					(0.005)	(0.006)	(0.007)	(0.009)
Joint test: num. of dry months + (num. of dry months x BCCT) = 0	-0.007	-0.010	-0.009	-0.013	-0.008	-0.011	-0.010	-0.015
F-statistic	0.839	1.306	0.820	0.781	0.921	1.507	0.973	1.022
p-value	[0.360]	[0.253]	[0.365]	[0.377]	[0.337]	[0.220]	[0.324]	[0.312]
Observations	23,108	16,954	11,889	6,145	23,108	16,954	11,889	6,145
R-squared	0.118	0.118	0.134	0.159	0.118	0.118	0.134	0.159

Notes: The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. All samples are restricted to respondents in agriculture-dependent communities. Column (1) and (5) reports all respondents in agricultural-dependent communities. Columns (2) and (6) report results from subsamples for agricultural-dependent communities and in the three lowest wealth quintiles. Columns (3) and (7) report results from subsamples for agricultural-dependent communities and in the three lowest wealth quintiles. Columns (4) and (8) report results from subsamples for agricultural-dependent communities and in the three lowest wealth quintiles. BCCT project is a dummy variable that equals to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted. Inactive BCCT project is a dummy variable that equals one if there is a known future BCCT project in a sub-district, but that had not yet been established at the time of the survey. 'num of BCCT projects' is the number of BCCT projects implemented before the survey and 'num of inactive projects' is the number of projects that will be implemented after the survey year in a particular sub-district. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. *p*-values in square brackets. ***p<0.01, **p<0.05, *p<0.1.

Appendix

Figure A1: The location of aid projects in Bangladesh, 2000-2015



Notes: Figure A1, constructed by the authors, shows the location of aid projects in Bangladesh for the period 2000-2015 based on "*Bangladesh Select Donors Geocoded Research Release, Version 1.1.1.*", released in April 2016. See text for further details.

Table A1: The effects of climate shocks

	Dependent Variable: Justifies IPV for at least one reason Sample restricted to:					
	All	Agriculture Dependent Communities	Non Agriculture Dependent Communities	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Number of dry months (in logs)	0.028	0.064**	-0.087	0.048*	0.068**	0.115***
	(0.025)	(0.027)	(0.053)	(0.027)	(0.031)	(0.039)
Observations	47,885	23,108	22,608	27,085	17,703	8,657
R-squared	0.110	0.118	0.120	0.112	0.131	0.157
Panel B						
Number of dry months	0.018**	0.033***	-0.014	0.020**	0.024**	0.038***
	(0.008)	(0.009)	(0.016)	(0.009)	(0.009)	(0.014)
Years lived in same residence	0.001	0.001	0.000	0.001*	0.001	0.002*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	17,214	8,461	7,970	9,856	6,534	3,253
R-squared	0.099	0.114	0.113	0.103	0.124	0.144
Panel C						
Number of dry months	0.035**	0.027*	-0.015	0.049***	0.045**	0.065**
(second quartile)	(0.015)	(0.015)	(0.024)	(0.015)	(0.018)	(0.025)
Number of dry months	0.033	0.053**	-0.025	0.048**	0.044*	0.103***
(third quartile)	(0.022)	(0.025)	(0.033)	(0.022)	(0.024)	(0.035)
Number of dry months	0.034	0.059**	-0.035	0.059**	0.072**	0.126***
(fourth quartile)	(0.028)	(0.029)	(0.046)	(0.026)	(0.033)	(0.046)
Observations	47,885	23,108	22,608	27,085	17,703	8,657
R-squared	0.111	0.118	0.120	0.113	0.131	0.157

Notes: The table shows the coefficients on the variables for climate shocks. The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. Column (1) reports full sample results. Columns (2) and (3) report results from subsamples for agricultural-dependent and non-agricultural-dependent communities. Columns (4), (5) and (6) report results from subsamples for the three poorest, two poorest, and the poorest quantiles. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A2: The effects of climate shocks: Additional weather controls

	Dependent Variable: Justifies IPV for at least one reason					
	Sample restricted to:					
	All	Agriculture-Dependent Communities	Non-Agriculture-Dependent Communities	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Number of dry months (past 3 years)	0.005	0.010**	-0.008	0.009**	0.011**	0.016**
(below 1 SD of historical average rainfall)	(0.004)	(0.005)	(0.008)	(0.004)	(0.005)	(0.007)
Number of wet months (past 3 years)	-0.004	-0.002	0.002	-0.007	-0.004	0.000
(above 1 SD of historical average rainfall)	(0.004)	(0.005)	(0.011)	(0.005)	(0.006)	(0.008)
Number of hot months (past 3 years)	-0.002	-0.008*	-0.002	-0.004	-0.007	-0.009
(above 1 SD of historical average temperature)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)	(0.007)
Solar radiation (past 3 years)	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wind speed (past 3 years)	0.028	-0.068	0.045	0.009	0.006	-0.030
	(0.036)	(0.042)	(0.069)	(0.040)	(0.044)	(0.050)
Vapor pressure (past 3 years)	-0.047**	-0.005	-0.053	-0.045*	-0.042	0.015
	(0.023)	(0.026)	(0.057)	(0.025)	(0.026)	(0.032)
Observations	47,885	23,108	22,608	27,085	17,703	8,657
R-squared	0.111	0.118	0.120	0.113	0.131	0.157

Notes: The table shows the coefficients on the variables for climate shocks. The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. Column (1) reports full sample results. Columns (2) and (3) report results from subsamples for agricultural-dependent and non-agricultural-dependent communities. Columns (4), (5) and (6) report results from subsamples for the three poorest, two poorest, and the poorest quantiles. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A3: The effects of climate shocks on tolerance of IPV in agriculture

Dependent Variable: Justifies IPV for at least one reason				
		Sample restricted to:		
	All	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)
Panel A: Sample restricted to agricultural households				
Number of dry months (past 3 years)	0.016***	0.014**	0.019***	0.028***
(below 1 SD of historical average rainfall)	(0.006)	(0.006)	(0.007)	(0.010)
Observations	12,864	10,517	7,557	3,902
R-squared	0.127	0.132	0.154	0.198
Panel B: Sample restricted to other households				
Number of dry months (past 3 years)	-0.001	0.005	0.005	0.005
(below 1 SD of historical average rainfall)	(0.005)	(0.006)	(0.008)	(0.011)
Observations	34,435	16,293	9,970	4,637
R-squared	0.115	0.124	0.151	0.195
Panel C: Sample restricted to agricultural households and women are employed				
Number of dry months (past 3 years)	0.005	-0.001	0.001	0.034*
(below 1 SD of historical average rainfall)	(0.009)	(0.010)	(0.012)	(0.018)
Observations	4,698	3,991	2,941	1,543
R-squared	0.158	0.166	0.194	0.240
Panel D: Sample restricted to agricultural households and women are not employed				
Number of dry months (past 3 years)	0.018**	0.020***	0.026***	0.032**
(below 1 SD of historical average rainfall)	(0.007)	(0.008)	(0.010)	(0.016)
Observations	8,112	6,470	4,542	2,279
R-squared	0.142	0.151	0.174	0.220

Notes: The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A4: The effects of climate shocks on other indicators

	Sample restricted to: Agricultural households in the lowest quintile Dependent variable:			
	No participation in decision-making (1)	Decision-making index (2)	free of movement (3)	control over earnings (4)
Panel A (Agricultural households)				
Number of dry months (past 3 years)	0.018*	-0.014*	0.001	-0.023**
(below 1 SD of historical average rainfall)	(0.010)	(0.008)	(0.012)	(0.009)
Number of wet months (past 3 years)	0.014	-0.004	-0.020	-0.008
(above 1 SD of historical average rainfall)	(0.013)	(0.006)	(0.013)	(0.009)
Number of hot months (past 3 years)	0.027**	-0.007	0.019	-0.003
(above 1 SD of historical average temperature)	(0.013)	(0.006)	(0.012)	(0.007)
Observations	999	2,863	1,000	2,371
R-squared	0.162	0.121	0.203	0.095
Panel B (Women employed in agriculture)				
Number of dry months (past 3 years)	0.034***	-0.017**	0.018	-0.019*
(below 1 SD of historical average rainfall)	(0.013)	(0.008)	(0.014)	(0.010)
Number of wet months (past 3 years)	0.004	-0.001	-0.003	-0.004
(above 1 SD of historical average rainfall)	(0.018)	(0.007)	(0.014)	(0.010)
Number of hot months (past 3 years)	0.038**	-0.005	0.020	-0.006
(above 1 SD of historical average temperature)	(0.019)	(0.006)	(0.014)	(0.007)
Observations	735	2,514	736	2,060
R-squared	0.194	0.134	0.250	0.102
Individual and household controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
District FE	✓	✓	✓	✓
Month, year of survey FE	✓	✓	✓	✓

Notes: The table shows the coefficients for the climate shocks variables. In column (1), the dependent variable is set to one if the respondent does not participate in any of the four decisions related to her own healthcare, major household purchases, visits to her family or relatives, and child healthcare, using data only from the 2011 and 2014 DHS waves. Column (2) employs a decision-making index, representing an average of her responses to the three first decision-related questions using data across the three DHS waves. Column (3) includes a "freedom of movement" indicator, assigned a value of one if the respondent reports having the freedom to visit the health center alone or with her children. In column (4), the dependent variable is equal to one if she replies "jointly" when asked about "who usually decides how to spend the respondent's earnings". In Panel A, we consider agricultural households in which either the respondent or her husband is employed in agriculture. In Panel B, we consider the sub-sample of women whose main occupation is in the agricultural sector. All regressions include the same controls used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A5: Summary statistics for sub-districts with and without BCCT projects

	Non-BCCT		BCCT		
	Mean	Std. Dev	Mean	Std. Dev	Difference
	(1)	(2)	(3)	(4)	(5)
Social, economic, and geographic covariates					
Nightlight (in logs)	1.527	1.235	1.216	0.681	0.311***
NDVI (in logs)	8.448	0.175	8.461	0.212	-0.013
Ground slope	0.347	0.762	0.223	0.244	0.124**
Elevation	21.657	32.903	15.157	14.124	6.500**
Population density	7.287	1.345	6.964	0.482	0.323***
Distance to coast (km)	163.650	112.120	136.517	118.178	27.133*
Distance to roads (km)	2.290	2.138	2.413	2.392	-0.122
Travel time to cities (mins)	101.166	75.717	130.702	95.187	-29.536**
PM 2.5	39.571	6.229	38.021	5.995	1.549**
Share of employment in agriculture	53.838	26.200	54.857	17.799	-1.019
Share of employment in manufacturing	11.232	10.213	10.492	8.268	0.741
Share of employment in services	34.931	19.415	34.652	14.046	0.279
Households with access to electricity (%)	53.293	25.536	52.639	20.346	0.654
Population aged 15 to 64 years (%)	60.719	5.908	59.464	3.916	1.256**
Households with no access to toilet (%)	8.276	9.903	7.001	7.923	1.275
Climate change vulnerability indices					
Population affected by natural disasters	0.464	0.092	0.511	0.091	-0.048***
Heat stress	0.382	0.061	0.382	0.062	0.000
Land availability for livestock	0.364	0.048	0.382	0.047	-0.018***
Water availability	0.573	0.063	0.544	0.077	0.029***
Crop yield availability	0.532	0.046	0.529	0.048	0.003
Decrease in livestock & poultry health	0.647	0.041	0.631	0.046	0.016***
Land availability for agriculture	0.557	0.113	0.572	0.094	-0.015
Change in fish culture	0.250	0.100	0.297	0.084	-0.047***
Change in fish capture	0.290	0.108	0.331	0.093	-0.041***
Rail network vulnerability	0.335	0.127	0.365	0.113	-0.030*
Road network vulnerability	0.352	0.081	0.389	0.060	-0.037***

Notes: The table contains data on 544 sub-districts based on the information available from various sources. There are 138 sub-districts that were allocated a BCCT project at least once after 2010. Columns (1)-(4) show the summary statistics for the subsamples of Non-BCCT and BCCT recipients, respectively. Column (5) reports the difference in means between these groups, with the respective statistical significance. The data used to construct the social, economic, and geographic covariates are drawn from multiple sources including the 2001 and 2011 censuses, the NOAA National Geophysical Data Center, CGIAR-CSI, NASA LAADS DAAC, CIESIN, GHSHHG, and the Malaria Atlas Project, amongst others. The climate vulnerability indices, published in the official report "Nationwide Climate Vulnerability Assessment in Bangladesh", are constructed using 30-year historical data. ***p<0.01, **p<0.05, *p<0.1.

Table A6: Climate shocks, attitudes towards IPV and BCCT projects

	Dependent Variable: Justifies IPV for at least one reason Sample restricted to:					
	All	Agriculture-Dependent Communities	Non-Agriculture-Dependent Communities	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Number of dry months (past 3 years) (below 1 SD of historical average rainfall)	0.005	0.011**	-0.009	0.009*	0.011**	0.017**
	(0.004)	(0.005)	(0.008)	(0.005)	(0.006)	(0.007)
BCCT project (active before survey)	-0.008	0.062*	-0.061	-0.019	-0.012	-0.014
	(0.028)	(0.036)	(0.065)	(0.035)	(0.041)	(0.057)
Number of dry months x BCCT project	-0.002	-0.018**	0.017	-0.001	-0.002	-0.005
	(0.005)	(0.008)	(0.015)	(0.006)	(0.008)	(0.011)
Observations	47,885	23,108	22,608	27,085	17,703	8,657
R-squared	0.111	0.118	0.120	0.113	0.131	0.157

Notes: The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. Column (1) reports full sample results. Columns (2) and (3) report results from subsamples for agricultural-dependent and non-agricultural-dependent communities. Columns (4), (5) and (6) report results from subsamples for the three poorest, two poorest, and the poorest quantiles. BCCT project is a dummy variable that equals to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A7: Climate shocks, attitudes towards IPV and BCCT projects

	Dependent Variable: Justifies IPV for at least one reason					
	Sample restricted to: lowest quintile					
	respondent works in agriculture	resp. or husband in agriculture	husband in agric. and resp. works in any sector	respondent works in agriculture	resp. or husband in agriculture	husband in agric. and resp. works in any sector
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Number of dry months (past 3 years)	0.026*	0.022*	0.040**	0.023	0.020	0.040**
(below 1 SD of historical average rainfall)	(0.014)	(0.013)	(0.018)	(0.014)	(0.013)	(0.019)
BCCT project (active before survey)	0.135*	0.111	0.146			
	(0.070)	(0.071)	(0.113)			
Number of dry months x BCCT project	-0.046***	-0.038***	-0.042**			
	(0.013)	(0.013)	(0.020)			
Number of BCCT projects				0.052	0.034	0.121
				(0.041)	(0.047)	(0.080)
Number of dry months x num of BCCT projects				-0.022**	-0.018*	-0.032*
				(0.010)	(0.010)	(0.017)
Joint test: num. of dry months + (num. of dry months x BCCT) = 0	-0.021	-0.016	-0.002	0.001	0.003	0.001
F-statistic	1.560	0.960	0.010	0.000	0.030	0.170
p-value	[0.212]	[0.328]	[0.937]	[0.952]	[0.859]	[0.677]
Observations	2,470	2,800	1,543	2,470	2,800	1,543
R-squared	0.194	0.199	0.241	0.193	0.198	0.241

Notes: The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. *BCCT project* is a dummy variable that equals to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted. *Inactive BCCT project* is a dummy variable that equals one if there is a known future BCCT project in a sub-district, but that had not yet been established at the time of the survey. '*num of BCCT projects*' is the number of BCCT projects implemented before the survey and 'num of inactive projects' is the number of projects that will be implemented after the survey year in a particular sub-district. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. *p*-values in square brackets. ***p<0.01, **p<0.05, *p<0.1.

Table A8: Climate shocks, attitudes towards IPV and BCCT projects

	Dependent Variable: Justifies IPV for at least one reason		
	Sample restricted to: Respondents in agriculture-dependent communities		
	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)
Panel A: With pre-BCCT covariates			
Number of dry months (past 3 years)	0.011**	0.012*	0.024***
(below 1 SD of historical average rainfall)	(0.005)	(0.006)	(0.009)
BCCT project (active before survey)	0.086**	0.045	0.110
	(0.041)	(0.045)	(0.070)
Number of dry months x BCCT project	-0.021**	-0.021**	-0.040***
	(0.009)	(0.010)	(0.014)
Observations	16,954	11,889	6,145
R-squared	0.120	0.136	0.161
Panel B: Only projects still active			
Number of dry months (past 3 years)	0.010*	0.010*	0.021**
(below 1 SD of historical average rainfall)	(0.005)	(0.006)	(0.008)
BCCT project (active at survey)	0.067	0.025	0.054
	(0.041)	(0.048)	(0.074)
Number of dry months x BCCT project	-0.020**	-0.021**	-0.033**
	(0.008)	(0.010)	(0.014)
Observations	16,954	11,889	6,145
R-squared	0.118	0.134	0.159
Panel C: No projects in survey year			
Number of dry months (past 3 years)	0.010**	0.011*	0.022***
(below 1 SD of historical average rainfall)	(0.005)	(0.006)	(0.008)
BCCT project (active before survey)	0.117***	0.092*	0.130
	(0.043)	(0.047)	(0.080)
Number of dry months x BCCT project	-0.027***	-0.029***	-0.043***
	(0.009)	(0.010)	(0.016)
Observations	16,954	11,889	6,145
R-squared	0.118	0.134	0.159

Notes: The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. *BCCT project* is a dummy variable that equals to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted. *Inactive BCCT project* is a dummy variable that equals one if there is a known future BCCT project in a sub-district, but that had not yet been established at the time of the survey. '*num of BCCT projects*' is the number of BCCT projects implemented before the survey and '*num of inactive projects*' is the number of projects that will be implemented after the survey year in a particular sub-district. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A9: Climate shocks, attitudes towards IPV and BCCT projects: Nearest-neighbor matching estimator results

	Dependent Variable: Justifies IPV for at least one reason Sample restricted to: Respondents in agriculture-dependent communities			
	(1)	(2)	(3)	(4)
Number of dry months (past 3 years)	0.017	0.014	0.016	0.013
(below 1 SD of historical average rainfall)	(0.013)	(0.013)	(0.012)	(0.013)
BCCT project (active before survey)	-0.008	-0.020		
	(0.060)	(0.062)		
Number of dry months x BCCT project	-0.008	-0.006		
	(0.013)	(0.013)		
Inactive BCCT project (active after survey)		-0.090		
		(0.086)		
Number of dry months x inactive BCCT project		0.011		
		(0.012)		
Number of BCCT projects			0.000	-0.007
			(0.047)	(0.048)
Number of dry months x num of BCCT projects			-0.006	-0.005
			(0.011)	(0.011)
Number of inactive BCCT projects				-0.065
				(0.064)
Number of dry months x num of inactive projects				0.008
				(0.009)
Observations	4802	4802	4802	4802
R-squared	0.189	0.190	0.189	0.190

Notes: This table presents post-matching estimates of equation (3). Respondents whose sub-district received at least one active BCCT project (treated) are matched to all other respondents (control) based on their individual characteristics, including age of the woman and her spouse, religion, rural residency, and age of the first child. Nearest neighbor matching is performed without replacement such that all treated respondents are matched to one control respondent. The dependent variable is a dummy variable that equals one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. BCCT project is a dummy variable that equals one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted. Inactive BCCT project is a dummy variable that equals one if there is a known future BCCT project in a sub-district, but had not yet been established at the time of the survey. "num of BCCT projects" is the number of BCCT projects implemented before the survey and "num of inactive projects" is the number of projects that will be implemented after the survey year in a particular sub-district. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis of Table 2 and described in the text. All regressions are OLS and are weighted by sampling weights. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A10: Climate shocks, attitudes towards IPV and aid projects: BCCT and other

Dependent Variable: Justifies IPV for at least one reason						
	Sample restricted to: Respondents in agriculture-dependent communities					
	Three lowest quintiles	Two lowest quintiles	Lowest quintile	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Number of dry months (past 3 years)	0.013**	0.013**	0.020**	0.014***	0.014**	0.022***
(below 1 SD of historical average rainfall)	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)	(0.008)
Other development project (within 10 km)	0.044	0.032	-0.006	0.041	0.034	-0.006
(active before survey and ongoing)	(0.033)	(0.039)	(0.054)	(0.034)	(0.039)	(0.055)
Number of dry months x Other development project	-0.009**	-0.008	-0.002	-0.009*	-0.009	-0.002
	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)	(0.008)
BCCT project (active before survey and ongoing)				0.071*	0.033	0.080
				(0.040)	(0.046)	(0.074)
Number of dry months x BCCT project				-0.019**	-0.019**	-0.035**
				(0.008)	(0.010)	(0.014)
Observations	16,954	11,889	6,145	16,954	11,889	6,145
R-squared	0.118	0.134	0.158	0.118	0.134	0.159
Panel B						
Number of dry months (past 3 years)	0.009*	0.009	0.019**	0.010*	0.010	0.021**
(below 1 SD of historical average rainfall)	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)	(0.008)
Number of other development projects (within 10 km)	0.001	-0.003	-0.003	0.001	-0.003	-0.003
(active before survey and ongoing)	(0.008)	(0.010)	(0.012)	(0.008)	(0.010)	(0.012)
Number of dry months x num of other dev. Projects	-0.000	0.001	0.001	-0.000	0.000	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Number of BCCT projects				0.055*	0.030	0.072
				(0.033)	(0.035)	(0.051)
Number of dry months x Num of BCCT projects				-0.016**	-0.016*	-0.030**
				(0.007)	(0.009)	(0.012)
Observations	16,954	11,889	6,145	16,954	11,889	6,145
R-squared	0.117	0.134	0.158	0.118	0.134	0.159

Notes: The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. *BCCT project* is a dummy variable that equals to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted, and that was still active at the time of the survey. '*Other development projects*' is a dummy variable that equals to one if there was an ongoing development assistance project within 10 km of the respondent's cluster. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A11: BCCRF's projects

Projects	Objectives	Achievements (end of reporting period, 2016)	Achievements in 2012
(1) The Emergency 2007 Cyclone Recovery and Restoration Project (ECRRP)	Improve climate resilience of coastal populations to tropical cyclones	Full implementation targets met by end of 2015. Construction of 61 cyclone shelters; 11.5 km of access road.	Approved in May 2011; grant of $25 million; activities to start in 2012
(2) The BCCRF Secretariat	To improve the Ministry's capacity to manage climate change activities through a secretariat	Project completed on schedule as planned.	Establishment approved in February 2011; grant of $0.2 million in November 2011
(3) The Community Climate Change Project (CCCP)	Increase climate change resilience of selected communities by enhancing capacity	41 NGO executed projects, all completed. All targets met or exceeded; involving community-based efforts.	Allocation of $12.5 million in June 2011; grant agreement signed in early 2012
(4) The Climate Resilient Participatory Afforestation and Reforestation Project (CRPARP)	Reduce forest degradation; increase forest coverage; build long-term resilience in selected coastal and hilly communities	17,500 ha of land restored or reforested; 2000 kms of strip plantations established; 3.6 million workdays of community jobs, more than 60, 000 direct beneficiaries.	Approved in April 2011; Grant agreement of $33.8 million signed in 2012; activities to begin shortly after
(5) The Rural Electrification and Renewable Energy Development Project II (RERED II)	Increase access to clean energy in rural areas; use of renewable energy; promote more efficient energy consumption	489 solar irrigation pumps; 35, 062 acres covered, and 11,453 farmers directly impacted; met 100% of coverage target	Approved in September 2012; grant of $10 million

Source: Authors' compilation from the official BCCRF Annual Reports, 2011-2016, Washington, D.C.: World Bank Group.

Table A12: Climate shocks, attitudes towards IPV and BCCT Projects

	Dependent Variable: Justifies IPV for at least one reason		
	Sample restricted to: Respondents in agriculture-dependent communities		
	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)
Number of dry months (past 3 years)	0.010*	0.011*	0.022***
(below 1 SD of historical average rainfall)	(0.005)	(0.006)	(0.008)
BCCT project (active before survey)	0.081*	0.045	0.042
	(0.048)	(0.054)	(0.080)
Number of dry months x BCCT project	-0.024**	-0.022**	-0.029**
	(0.009)	(0.011)	(0.015)
Joint test:			
num. of dry months + (num. of dry months x BCCT) = 0	-0.013	-0.011	-0.008
F-statistic	1.88	0.95	0.25
p-value	[0.171]	[0.331]	[0.619]
Observations	16,522	11,560	5,977
R-squared	0.119	0.135	0.160

Notes: The dependent variable is a dummy variable that equals to one if the respondent says that she agrees that wife beating is justified for at least one of the five reasons given. *BCCT project* is a dummy variable that equals to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted. We exclude from the sample of respondents those who received all three types of projects - BCCT, other development assistance, and BCCRF projects. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. *p*-values in square brackets. ***p<0.01, **p<0.05, *p<0.1.

Table A13: The impact of BCCT and other active projects

	Sample restricted to: Respondents in agriculture-dependent communities							
	All	Three lowest quintiles	Two lowest quintiles	Lowest quintile	All	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	Dependent Variables:							
	Access to media				Microfinance program			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BCCT project (=1)	0.034**	0.023	0.031*	0.020	-0.054	-0.047	0.003	0.005
(active at survey)	(0.016)	(0.019)	(0.019)	(0.018)	-0.042	-0.053	-0.069	-0.096
Other development project (=1)	0.012	0.002	0.000	0.001	0.009	0.023	0.032*	0.046*
(active at survey)	(0.010)	(0.011)	(0.011)	(0.010)	-0.013	-0.016	-0.019	-0.027
Observations	23,265	17,073	11,988	6,203	14,608	10,626	7,358	3,731
R-squared	0.248	0.136	0.092	0.080	0.095	0.102	0.118	0.157
	Earns cash				Toilet facilities share			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
BCCT project (=1)	0.044**	0.054**	0.061**	0.062	-0.008	-0.010	-0.038	-0.053
(active at survey)	(0.020)	(0.023)	(0.028)	(0.042)	(0.017)	(0.022)	(0.028)	(0.042)
Other development project (=1)	-0.005	0.005	0.004	-0.013	-0.005	0.002	-0.009	0.015
(active at survey)	(0.016)	(0.018)	(0.021)	(0.031)	(0.011)	(0.013)	(0.016)	(0.024)
Observations	8,947	7,037	5,131	2,733	22,400	16,220	11,195	5,614
R-squared	0.211	0.222	0.233	0.237	0.094	0.099	0.118	0.161
	Transport				Electricity			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
BCCT project (=1)	0.030*	0.049**	0.069***	0.092***	-0.011	-0.017	0.028	0.058**
(active at survey)	(0.017)	(0.020)	(0.023)	(0.030)	(0.015)	(0.019)	(0.022)	(0.025)
Other development project (=1)	0.014	-0.008	-0.013	-0.009	0.030***	0.023**	0.011	-0.023
(active at survey)	(0.010)	(0.012)	(0.014)	(0.017)	(0.010)	(0.012)	(0.013)	(0.014)
Observations	23,284	17,088	11,995	6,204	23,284	17,088	11,995	6,204
R-squared	0.232	0.211	0.207	0.222	0.337	0.310	0.348	0.331

Notes: The dependent variables are six individual-level outcomes: access to media, access to microfinance programs, whether she earns cash, share of toilet facilities in the community, access to transportation vehicles (bicycle, motorcycle, or car), and access to electricity. BCCT project is a dummy variable that equals to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted, and that was still active at the time of the survey. 'Other development projects' is a dummy variable that equals to one if there was an ongoing development assistance project within 10 km of the respondent's cluster. Access to media equals to one if the respondent has access to information via one of the following ways: television, radio, newspaper. Microfinance is coded as one if the respondent has access to at least one form of microfinance programs. Transport is a dummy variable that equals one if she uses one of the following modes of transport: bicycle, motorcycle, or car. Earns cash, toilet facilities shared, and electricity are also dummy dependent variables. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.