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IZA DP No. 17529

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ABSTRACT

Climate Shocks, Intimate Partner Violence, and the Protective Role of Climate-Resilience Projects*

This study investigates the impact of climate change on intimate partner violence in Bangladesh and shows that policy can mitigate much if not all of the harmful consequences of climate shocks on women. Utilizing a novel dataset linking geo-referenced meteorological remote-sensed data with information on women's agency from the Bangladesh Demographic and Health Surveys, we find that dry shocks increase tolerance for intimate partner violence among women in poor and agriculture-dependent communities, amplifying existing social and environmental vulnerabilities. Climate resilience projects funded by the Bangladesh Climate Change Trust (BCCT), a domestic climate fund, mitigate the negative impacts of dry shocks, highlighting the important role of such initiatives in generate positive spillover effects in ameliorating the negative social impacts of changing climate. We show that impacts are mitigated as these projects enhance resilience in agriculture by reducing the effects of droughts on acreage and yield in rainfed areas. Our findings underline the role of targeted policy interventions in fostering climate adaptation and wellbeing.

JEL Classification: Q54, J16, O13

Keywords: climate change, women's agency, intimate partner violence, adaptation, mitigation, resilience, agriculture, Bangladesh

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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. 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.

The economic literature has demonstrated the diverse implications of climate shocks on outcomes in developing country settings, for instance in agriculture and livelihood (Aragon et al. 2021), effects on mortality (Burgess et al. 2017, Banerjee and Maharaj 2020), labor allocation (Liu et al. 2023), as well as on interpersonal or intergroup conflict (Hsiang et al. 2013; Burke et al. 2015, 2024). Despite this, gender-differentiated impacts of climate change are still an understudied area even as climate-related environmental shocks manifest through existing socioeconomic and gender inequalities in developing countries where coping mechanisms are scarce. In the comprehensive meta-analyses by Burke et al. (2015) and Burke et al. (2024), a total of 129 climate-conflict studies were included, but only seven are about gender-based violence, and only one study (Sekhri and Storeygard 2014) is based outside the developed world. At the same time, while communities, policy-makers, and international agencies strive to find effective ways to buffer the impacts of climate change through providing access to cooling technology (Deschenes and Greenstone 2011, Evans et al. 2024), healthcare support (Banerjee and Maharaj 2020, Mullins and White 2020), or land tenure reforms (Ajefu and Abiona 2020), 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 diverge across existing socio-economic structures. As is widely accepted, these attitudes may be viewed as measures of social norms (Jayachandran 2015). Our empirical analyses focus on Bangladesh, a developing country that is amongst the most susceptible to changing climate. 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 IPV in Bangladesh is relatively high, with 73% of ever-married women experiencing one or more forms of IPV at least once in their lifetime (Bangladesh Bureau of Statistics, 2016). Alternatively, over one-third of men aged between 15-49 agree that wife-beating is justified for several reasons (DHS, 2007). Our research aims to unravel the nuanced effects of climate-induced risks for women in an environment that is particularly susceptible.

Our second objective is to identify the extent to which climate resilience initiatives attenuate these negative impacts. During our study period, the Bangladeshi government implemented the Bangladesh Climate Change Trust (BCCT), a domestically-funded scheme that reflects its commitment to fostering climate resilience. BCCT financed community-based projects that promote climate adaptation and resilience, with a proportion of projects directly focused on women. Our study evaluates how effective these BCCT projects are at attenuating the harmful impacts of climate shocks on women's wellbeing, and probes mechanisms that lead to their effectiveness. To the best of our knowledge, ours is the earliest paper to empirically evaluate the effects of nationally-led investments that build resilience and foster adaptation, in a resource-constrained context situated at the epicenter of climate change.

We accomplish these objectives by constructing a novel dataset linking gridded data on rainfall, temperature, other climatic variables, and individual-level data on norms and women's agency. We obtain geo-referenced monthly meteorological remote-sensed data at a spatial resolution of 0.1° x 0.1° spanning 1980-2020 through. We combine this data with women's perspectives on and experiences of IPV, participation in decision-making, and control over earnings and other measures from four waves of the Bangladesh Demographic and Health Surveys (BDHS). Our empirical strategy leverages a widely used design in the climate impact literature that controls for unobserved heterogeneity, regional trends, and location-specific seasonality. Specifically, we follow the 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 (village)-specific averages 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 when rainfall realization was at least one standard deviation below the historical monthly average (the magnitude of this shock is consistent with other recent studies such as Abiona and Foureaux-Koppensteiner 2018), over the 1980-2000 time period. We construct similar intensity variables for months of wet spells (when rainfall is at least one standard deviation higher than the cluster-specific historical mean) and for months of heat waves (when temperatures are at least one standard deviation higher than the cluster-specific historical mean). We additionally include 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 among 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, all results are concentrated among poor women and those who live in agriculture-dependent communities. A one-standard-deviation increase in the frequency of dry months raises the likelihood that women in the lowest wealth quintile agree that wife-beating is justified by 4.3 percentage points. For women in agriculture-dependent communities, the comparable increase is 2.5 percentage points. There are few measurable effects for wet or hot months. The relative significance of dry shocks may be due to the fact that the country has a long history of adapting to floods and related wet shock events through community preparedness and infrastructural investments in embankments and drainage systems. We think that the insignificance of heat waves may be due to the correlation between rainfall and temperature in that excess heat may reduce rainfall (leading to dry shocks) through its effects on the content of moisture in the atmosphere. We are not the first to find that mainly dry shocks matter, and we discuss these factors in detail below. Our results withstand a battery of robustness checks, and we undertake heterogeneity analyses to reveal that droughts have larger negative impacts on the poorest women in agriculture-dependent communities.

In order to accomplish our second goal of evaluating whether climate-resilience initiatives mitigate the negative impacts of environmental shocks, we digitized the list of BCCT projects from official sources, including their location at the sub-district or *upazila* level, and timing of initiation and ending. Our results indicate that proximity to a BCCT project almost completely counteracts the effect of droughts in agricultural communities and across several wealth strata. These results remain even after we control for a host of pre-treatment covariates and employ a wide variety of tests to control for the possible endogeneity in project location. In particular, placebo tests find no significant attenuation effects for inactive (past or future) BCCT projects, and significant but smaller effects for other development assistance projects. Using remotely sensed satellite data on land use and crop yield indicators, we find that BCCT projects protect agricultural activities, especially rainfed *aman* season rice, from drought shocks. More specifically, proximity to BCCT projects buffers the negative impacts of drought on *aman* season normalized difference vegetation index, a proxy for rice yield, as well as the proportion of area planted with rainfed crops. Additionally, we find that BCCT projects play an important role in improving women's agency and wellbeing through access to cash earnings, media, transport facilities, and electricity.

Our paper makes several contributions to the literature. First, we complement the literature on the social impact of climate change in developing nations. Prior literature has shown impacts of climate change 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 and intra-group conflict (Hsiang et al. 2013, Burke et al. 2015, 2024, Ubilava et al. 2022, Maconga 2023). More specifically, we add to the smaller group of studies that analyze gender-based violence (Ranson 2014, Takahashi 2017, Sanz-Barbero et al. 2018, Mannell et al. 2024), especially in developing country contexts (Sekhri and Storeygard 2014, Cools et al. 2020, Sekhri and Hossain 2023, Díaz and Saldarriaga 2023, Nguyen 2024). Our study also carries implications for the climate and environmental justice literature (e.g., Banzhaf et al. 2019) in demonstrating differential impacts of climate shocks along existing social, economic, and cultural divides.

Secondly, our work contributes to policy debates on mechanisms that help to mitigate climate impacts (Ajefu and Abiona 2020, Barreca et al. 2016, Cohen and Dechezleprêtre 2017, Colmer and Doleac 2023, Evans et al. 2024, Hirvonen et al. 2023, Isen et al. 2017, Li 2023, Mullins and White 2020, Nguyen et al. 2022, Randazzo et al. 2023, Sarsons 2015, Rustad et al. 2020, Wang et al. 2024). Previous studies have examined factors such as cash transfers (Macours et al. 2022) and reducing losses (Pople et al. 2023) in building resilience in the developing world. The novelty of our study is that it evaluates the impact of domestically-funded climate-resilience initiatives designed to reduce vulnerability. Our finding 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 generate measurable positive spillover effects beyond the aims for which they are sanctioned.

Next, our work builds on the literature on gender equality and women's agency in the developing world, especially on effective ways to limit intimate partner violence. Importantly, our finding that climate resilience projects alleviate IPV complements the literature that considers socio-economic factors that either ameliorate IPV (Aizer 2010, Bobonis et al. 2013, Guimbeau et al. 2023), or intensify it through backlash effects (Heath 2014, Cools and Kotsadam 2017, Erten and Keskin 2024). Our findings also suggest that social norms on acceptance of IPV may be amenable to change in relatively short periods of time, which is contrary to the standard widespread belief that acceptable cultural and social "rules" of behavior for women are "sticky" and long-standing. This is a hopeful result with both current and inter-generational consequences that we hope to investigate further in future work.

Finally, we differ in an important aspect in that our study considers weather variables in unison. This is important since weather variables such as temperature and rainfall are likely correlated, hence focusing on one or the other in isolation could lead to inaccurate inference. For instance, prior work has documented the effects of rainfall shocks alone on dowry deaths (Sekhri and Storeygard 2014) or domestic violence (Abiona and Foureaux-Koppensteiner 2018, Cools et al. 2020, Díaz and Saldarriaga 2023, Dehingia et al. 2023, Epstein et al. 2020), or temperature shocks alone on intimate partner violence (Nguyen 2024). Consistent with recent developments in the literature (Zhang et al. 2017, Hanifi et al. 2022), we consider temperature and rainfall jointly while allowing for more flexible non-linear functional forms (in non-parametric specifications as well as quadratic forms).

2. Climate shocks and women's agency

The relationship between climate shocks, IPV, and women's agency is intricately tied to socio-economic shifts caused by environmental disruptions. These changes often lead to significant unforeseen income losses, alter traditional gender roles, and challenge established norms, impacting household dynamics.[1] This effect is particularly pronounced in vulnerable and marginalized communities, where women have fewer fallback options, and cultural and institutional factors may foster a higher tolerance for violence (Benson et al. 2013).[2] The literature provides rich theoretical insights into how climate change can impact women's agency, drawing connections between environmental stressors and socio-economic outcomes. This body of work underscores the importance of considering gender dynamics when assessing the broader implications of climate change, as we do in this study.

Extreme weather events intensify vulnerabilities, especially for those lacking access to essential resources, effective coping strategies and safety nets. Climate shocks during crucial agricultural seasons are specifically linked to major losses in income, affecting rural communities unevenly. Such increased vulnerability largely impacts women's wellbeing, thereby elevating their risk of experiencing IPV (Solotaroff et al. 2019). The stress from unexpected climate-induced income volatility can heighten household tensions and increase the likelihood of IPV. Further, economic pressures and resource shortages can trigger conflicts over finances (Díaz and Saldarriaga).[3]

Gender-biased social norms that assign caregiving and domestic tasks predominantly to women limit their job opportunities and restrict their access to stable, non-farm employment, reducing their ability to diversify income sources away from those heavily reliant on climate conditions (Afridi et al.

[1] Research shows that during climate shocks, there can be a significant reallocation of roles within households, acting as a potential catalyst for lasting gender role transformations and altered women's empowerment (Vitellozzi and Giannelli 2024).
[2] In such poorer communities, the communal backdrop can further impact the climate-IPV nexus due to weaker institutions.
[3] In rural areas of the Peruvian Andes, the effects of droughts are particularly severe. The direct impact of reduced income on consumption increases household stress, potentially leading to more frequent occurrences of IPV. Additionally, financial stress can increase alcohol consumption among men, further amplifying the risk of IPV (Díaz and Saldarriaga 2023).

2022, Escalante and Maisonnave 2022, FAO 2024).[4] Changes in societal beliefs toward gender equality, influenced by income shocks, might thus also affect women's tolerance toward violence. The complex relationship between climate shocks, economic stability, and gender norms plays a crucial role in shaping the prevalence and acceptance of IPV during times of hardship. Following climate events like droughts, women often see a decrease in employment opportunities, particularly in agriculture, reducing their financial independence and control over household finances. This economic dependence may shift intra-household power dynamics, thus increasing women's tolerance of abuse. In contexts with limited community support and restricted access to welfare services, very often severe financial constraints and diminished employment opportunities combine to undermine women's capacity to escape abusive situations (Farmer and Tiefenthaler 1997).

We note that the link between climate shocks and women's agency is influenced by relative shifts in household dynamics, as men may also be affected. This interdependency is why many household bargaining models emphasize changes in women's resources relative to men's. The loss in financial stability can make women more dependent on their partners, potentially leading to greater tolerance of IPV due to diminished autonomy and limited exit options following climate shocks. Conversely, if climate change disproportionately affects men's employment, it may prompt an increase in aggressive behavior as men reassert dominance. Such responses can emerge when men confront threats to their identity or are forced into non-traditional roles, consistent with backlash, status inconsistency, and

[4] These norms also perpetuate wage and productivity disparities, which further constrain women's economic mobility. As such, gender-based disparities in climate vulnerability arise from social structures and discriminatory practices that shape unequal access to resources, land ownership, job quality, and financial and agricultural services. These inequalities reduce women's adaptive capacity, confining them to livelihoods that are more climate-sensitive across multiple aspects (Source: FAO. 2024. *The unjust climate – Measuring the impacts of climate change on rural poor, women and youth.* Rome. https://doi.org/10.4060/cc9680en). Further, many adaptation strategies require substantial time commitments, making it harder for women to strike a balance between investing in such strategies and household burdens including childcare. In various social contexts, droughts can influence additional correlates of IPV, such as increasing the likelihood of early marriage (Corno et al. 2020), with significant implications for household bargaining power.

household bargaining theories (Aizer 2010, Bobonis et al. 2013, Bloch and Rao 2022, Eswaran and Malhotra 2011, Hidrobo and Fernald 2012, Hornung et al. 1981, Pollak 2005, Tauchen et al. 1999).

3. Background and data

Bangladesh is one of the largest populations at risk from climate change. Despite being responsible for only 0.56% of global CO_2 emissions (Hasan and Chongbo 2020), it ranks as the seventh most susceptible country to climate-related disasters.[5] Bangladesh's vulnerability is heightened by its geography which is characterized by a flat deltaic topography. Consequently, various parts of the country frequently face floods, strong cyclones, and the intrusion of saline water. These factors disproportionately affect at-risk communities given the relatively high incidence of poverty, high population density, and heavy reliance on agriculture.[6]

3.1. 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.[7] We build a repeated cross-sectional dataset and use the geographic coordinates of each surveyed cluster (village) across rounds to merge the geo-coded climate data as well as earth observation remote-sensed data. Figure 1 shows the location of BDHS clusters in 2007 (on the left), and for the three other years (on the right). We separate in this manner since 2007 is the only year in which we have a measure of the

[5] See the Global Climate Risk Index (CRI) of 2021 by Germanwatch, available at https://www.germanwatch.org/en/cri.
[6] Rural households in Bangladesh spend approximately US$2 billion annually on disaster preparedness and response, significantly outpacing the combined contributions of national government and international aid (Eskander and Steele 2019). Evidence suggests a stark contrast in financial responsibility for climate adaptation, with women bearing a higher economic burden than men. Eskander et al. (2022) finds that in a survey of 3,094 households in ten districts in Bangladesh, poor rural households allocate as much as 15% of their expenditure to mitigating climate-related risks, with female-headed households spending up to 30%.
[7] 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*.

actual experience of IPV, as we discuss in detail below. On average, each district contains 10 clusters, while there is an average of two clusters in each sub-district.

3.1.1. Women's attitude towards domestic violence

We use samples of women aged 15-49 from the 2011, 2014, and 2017 waves, with detailed information on individual and household characteristics, as well as measures on our outcomes of interest relating to gender attitudes, women's agency, and experience of IPV.[8]

We begin by using variables related to attitudes towards physical violence. 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). 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 husband; (iii) goes out without telling the husband; (iv) neglects the children; and (v) refuses to have sex. Following the literature, we create an index dummy variable that equals 1 if the woman agrees with at least one of these five statements.

Our study focuses on women's attitudes toward IPV, in line with established research methodologies (Bisika 2008, Mitra et al. 2021, Mwale 2023, Mwale et al. 2021, Thompson et al. 2007). This approach addresses the challenge of collecting accurate self-reported IPV data, particularly in traditional patriarchal settings like Bangladesh, where deeply ingrained gender norms may cause women to hesitate in disclosing abuse. Factors such as shame, fear of repercussions, increased violence or loss of family access (Mitra et al. 2021), often deter women from speaking openly about their experiences. Attitudes toward IPV significantly affect how women perceive and react to abuse, and attitudes may

[8]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 reported separately.

provide a more reliable measure of IPV prevalence given concerns of under-reporting due to cultural stigma. Indirect questions, such as inquiring whether IPV is justifiable, may thus provide more insights in cultures where open discussion of such abuse is taboo. This method of collecting information may also help mitigate issues associated with recall bias, enabling a clearer understanding of dynamics.

3.1.2. Experience of domestic violence

While the majority of our analyses use information on tolerance of IPV, we also use the domestic violence module available only in the 2007 BDHS to measure the experience of violence. This sample provides information on experience of physical or sexual violence.[9] There were 4,467 ever-married women and 3,374 ever-married men eligible to respond, and several measures were taken to safeguard their privacy.[10] We code dependent variables for the experience of physical and/or sexual violence, similar to the measure for acceptance of IPV described above.[11]

3.2. Weather variables

Raw weather data is obtained from the ECMWF Reanalysis v5 (ERA5), a reanalysis product that focuses on agrometeorological indicators including temperature, precipitation, air pressure, wind speed,

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[9] 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).

[10] 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.

[11] 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?"

and solar radiation, available at a spatial resolution of 0.1° x 0.1° (Boogaard et al. 2020).[12] We construct monthly averages for these variables from the daily time series and then match the latitude-longitude of each sampled DHS cluster to the geo-coded weather data.[13]

We use inverse-distance matching to obtain local measures of climate by calculating the weighted average of the 5 closest grid points, weighing each point by the inverse of the distance from a cluster's centroid. This approach is commonly used in the environmental economics literature (Mendelsohn et al. 1994, Deschenes and Greenstone 2011, Zhang et al. 2017). We check for robustness with 1, 3, and 10 closest grid points.

3.2.1. 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. 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 changes in the distribution of 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

[12] This dataset is also referred to as AgERA5 and is based on the hourly ECMWF ERA5 data series. The original file format is the Network Common Data Form (NetCDF-4). Python scripts were developed to retrieve and process weather data into monthly time series, which will be available on request.
[13] The distributions of the additional weather variables are also likely to be affected by climate change.

of the monsoon. Again, there is a noticeable change in the distribution over time. In Figures 2 (e) and 2 (f), we present the distributions of average annual monsoon rainfall. Shifts are again evident.[14]

Additionally, 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 levels have increased, signaling heightened variability as climate evolves (World Bank, 2021).[15]

3.3. 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. Our analyses of mechanisms use remote-sensed information including that on land use decisions using high-resolution (300m) Copernicus Land Monitoring Service (CLMS) sources, crop yield data from normalized difference vegetation indices (NDVI) constructed from MODIS's vegetation indices product (MOD13A3) available at a spatial resolution of 1 km, as well as nighttime light data from harmonized DMSP and VIIRS indicators by Li and Zhou (2017). We provide detailed explanations below.

To assess the potential mitigating effects of climate-resilience projects funded by the Bangladesh Climate Change Trust, we digitized the list of approved projects from the official Bangladesh National Portal. We acquire information related to project names, implementing agencies, estimated costs, start dates, as well as both scheduled and actual end dates for several projects. We also extracted location data from the project titles, supplementary documents available on the portal, and resources from the

[14] 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).

[15] "*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.

Ministry of Environment, Forest, and Climate Change. We elaborate on these sources in Section 6 below. Additional datasets used provide information on climate vulnerability indices, pre-treatment geographic and socio-economic covariates at the sub-district level, and other agency indicators.

3.4. 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. Those having control over their own earnings constitute 57% of the sample. 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, with 6% enduring both types. 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 4.4, with a standard deviation of 1.7 months.[16] Panel D shows the statistics for the set of controls used in all our regressions.

4. Empirical strategy

In constructing weather shocks, we follow the related literature and consider deviations of rainfall and temperature from their long-run local averages over the period 1980 through 2000. These shocks are often defined as extreme exogenous weather events, and may 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 monthly norm

[16] This is consistent with Tsaneva (2020). That study finds an average number of dry months for 12 months before survey of 1.2 with a SD of 1.2 (based on historical distribution for 1950-1999). We obtain an average of 1.7 with a SD of 1.1. 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.

by at least one standard deviation, and zero otherwise. Cluster-specific monthly norms are the 20-year cluster-average level of rainfall for that month. Similarly, we identify a heat shock as when monthly average temperature is at least 1 SD above the 20-year cluster-level average for that month; an excessive rain (wet) shock as when the rainfall that month exceeds the cluster-specific rainfall norm by at least 1 SD. The choice of 1 SD as a deviation metric is consistent with other studies (Dell et al. 2014, Abiona and Foureaux-Koppensteiner 2018, Ibanez et al. 2021), and we check for robustness of our deviation-based metric by running the analyses using the Standardized Precipitation Evapotranspiration Index (SPEI), an alternative drought and heat metric.[17]

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 a climate shock (drought, excessive rain, or extreme heat) occurred.[18] Our specification is:

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

where y_{icdmt} represents the outcome of interest for woman i in cluster c in district d in month m and year t. In our main model, 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, "0" otherwise. 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. W_{cdmt} is a vector of other climatic conditions that includes the number of wet shocks and temperature shocks during the past three years. This vector also includes weather variables at the time

[17] Estimation results using SPEI are presented in Table A1.

[18] 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 three reasons. First, we follow the literature as noted above. Second, we need an adequate time frame for the occurrence of climate shocks to potentially affect women's attitudes towards domestic violence. Third, we limit the time interval as adaptive responses may become important in the absence of an upper time bound.

of the survey. More specifically, 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 in 5°C intervals: (10-15]°C, (15-20]°C, (25-30]°C, and (30-35]°C. [19] The omitted temperature bin is (20-25]°C, 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} is thus as in equation (2):

$$W_{cdmt} = \tau numwetmths_{cdmt_{-36}} + \phi numhotmths_{cdmt_{-36}} + \sum \alpha^N temp^N_{cdmt} + \delta_1 rain_{cdmt} + \delta_2 rain^2_{cdmt} \qquad (2)$$

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, the 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 district-by month and district-by-year fixed effects. 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 time-varying 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, there are no omitted variables that are simultaneously correlated with the number of dry months and with women's attitudes towards IPV. In this empirical framework, weather shocks are as good as random.

5. Droughts increase women's acceptance of IPV

[19] 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 (LoPalo 2023, Zhang et al. 2017, Burke et al. 2015, Blom et al. 2022, Hanifi et al. 2022).

5.1. The impact of weather shocks on acceptance of IPV

Table 2 presents results from the main regression in equation (1). Column (1) shows results from the full sample; we find statistically insignificant impacts of dry shocks on women's acceptance of IPV. Columns (2) and (3) estimate effects by partitioning the sample using indicator variables for above and below median values of the share of employment in agriculture at the *upazila* level (using Census data from 2011), 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 in agriculture-dependent communities.[20] In communities not dependent on agriculture, we find no effect. We find no significant effects of higher frequencies of wet and hot months in both sub-samples.[21]

Why is it that only past droughts matter in a specification that takes past wet and heat shocks into account, as well as current temperature and rainfall? Focusing on wet shocks first, in Bangladesh,

[20] Research indicates a strong positive correlation between the tolerance of IPV and the actual experience of abuse. Uthman et al. (2011), for example, examines 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) identifies a significant positive correlation between women's attitudes towards IPV and the incidence of domestic violence in Nigeria. 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. The study concludes that attitudes towards violence are crucial indicators of IPV prevalence.

[21] In a 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 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. Dehingia et al. (2023) highlight the distinctions between precipitation-based droughts, estimated via remote-sensed data and GIS mapping, and socioeconomic drought, identified through government records. They find that women in drought-stricken regions of India are at an increased risk of experiencing IPV.

there is some level of longstanding proficiency in managing events such as floods given the country's geographical and historical context as a low-lying delta prone to such events, especially during the monsoon season. Over the years, extensive experience, community preparedness, investment in adaptive capacities, changes in individual choices, and robust infrastructure development including embankments and drainage systems, have bolstered resilience against floods.[22] Additionally, there has been significant international support in furthering local adaptation strategies such as the use of flood-resistant rice varieties that protect yields and household consumption in the country (Bairagi et al. 2021). Conversely, droughts present unique challenges due to their unpredictability, and the lack of visible and immediate impacts, which hinder rapid responses and resource mobilization. Bangladesh also has less developed infrastructure to manage water scarcity, which worsens the impacts of droughts. Our finding that primarily droughts have impacts is not unique. Díaz and Saldarriaga (2023), for instance, shows that adaptive capacities in the Peruvian Andes are not developed enough for managing droughts, but are effective in times of excessive rainfall through water management and other agricultural strategies.

What about heat shocks? Heat waves could affect IPV through at least two channels, and the estimated coefficient would in theory capture both effects: An income channel where heat intensifies the severity of drought by increasing evapotranspiration, thus diminishing income; and a physiological channel where heat leads to more aggressive behavior (Hsiang et al. 2013). Our data are not detailed enough for us to test the temperament channel. As to the income channel, which is more likely in

[22]Vitellozzi and Giannelli (2024) analyzes the impact of the 2017 Bangladesh flood on time allocation and empowerment, integrating data from the 2014 flood. Post-2017, women increasingly engaged in paid and leisure activities, with a decrease in domestic work. They also find that individuals affected by the 2014 flood adapted differently in 2017, demonstrating a climate change adaptive capacity through a "learning-by-doing" approach that helps mitigate the long-term effects of floods. Smith and Frankenberger (2018) assesses the resilience capacities that helped reduce the 2014 floods' impact on food security, highlighting the importance of social and human capital, as well as access to information and markets. Haque et al. (2022) highlights how social learning derived from firsthand experiences with floods has enabled wetland communities to strengthen resilience against flash floods, with innovations and shared experiences playing crucial roles in effective flood management.

agricultural settings, we may lose precision for heat shocks as heat and drought are correlated.[23] We also find support for this in the climate science literature where it has been noted that droughts and heatwaves have similar underlying factors in the face of accelerating climate change, thus driving the joint occurrence of "warm/dry" events (Hao et al. 2013, Naumann et al. 2021, Tripathy et al. 2023).

Returning to the discussion of results, we next break down the sample by respondents' wealth in columns (4)-(6). We find that vulnerable households are the most affected, and the magnitude of the impact rises with the extent of vulnerability.[24] 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, and about 4.3 percentage points for women in the poorest quintile.[25]

5.2. Robustness tests for the main results

5.2.1 Alternative specifications and additional controls

We consider additional checks in Table A1 to ensure the robustness of these results. In Panel A, we replace our exposure measure with the log number of dry months in the 3 years prior to the survey. We obtain qualitatively similar results. In Panel B, we address population sorting that could be partly driven by climate shocks by controlling for the number of years the respondent has lived in the current

[23] Extreme heat conditions are associated with less cloud cover and humidity, which, in turn, suggests less rainfall. Within our data, we find that in our data for Bangladesh, temperatures in the (25-30]°C and (30-35]°C bins are significantly positively correlated with rainfall (pair-wise correlation coefficients of 76% and 17% respectively, and statistically at the 95% level).

[24] We also examine separately regression results for each of the five wealth quintiles. Without conditioning on agricultural dependence, we find that the effects are primarily driven by the lowest quintile. This finding supports our focus on the lowest quintile in subsequent parts of our analysis.

[25] We also use the 2007 DHS wave separately as it includes data on men's attitudes towards IPV. We construct a similar binary dependent variable that equals one if the male respondent agrees with at least one of the reasons given for IPV. Given the limited sample size, we use region fixed effects, with a comparable set of individual and climatic controls as those used in the analysis of female respondents in Table 2. We do not find any significant effects of dry shocks, which may be the result of the relatively small sample size.

residence.[26] Our estimates remain for agricultural-dependent communities and for respondents in the three poorest quintiles, with larger magnitudes as compared to Table 2.[27]

In Panel C, we replace our variable of interest with exposure to quartiles of dry shocks.[28] We find that as compared 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 in households in the lower wealth quintiles.

Panel D reports results from a distributional lag model where we estimate the impacts of exposure within the past 12 months, between 13-24 months, and between 25-36 months. We find cyclical patterns that the results are mostly driven by exposures during the past 12 months and between 25-36 months. This result is qualitatively similar to Ji and Cobourn (2021), which also find cyclical impacts from past weather shocks (on agricultural land use).

Panel E uses the Standardized Precipitation Evapotranspiration Index (SPEI) as an alternative measure of drought and wet conditions.[29] We find qualitatively similar results: Drier/hotter conditions (SPEI<0) increase women's tolerance to IPV, whereas wetter/cooler conditions (SPEI>0) have no impact.[30]

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[26] The variable measuring the number of years lived in the current place of residence is available only in the 2017 wave. Thus, results in Panel B are restricted to these data.

[27] Results are also qualitatively similar when we restrict our sample to the poorest women who have been living in their current place of residence for more than 15 years (the median number of years of residence).

[28] 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.

[29] SPEI uses both precipitation and potential evapotranspiration (PET) to determining droughts, which captures the impact of increasing temperature on water demand (Vicente-Serrano et al., 2010, Beguería et al. 2014). Monthly SPEI measures are derived using temperature, precipitation, wind speed, vapor pressure, and solar radiation from the ERA5 weather series. We omit the number of hot months in the regression because temperature is already taken into consideration when calculating PET.

[30] The smaller the SPEI index (the larger in absolute value when SPEI<0), the hotter and drier the weather is. Hence the negative coefficients in Panel E correspond to increases in acceptance of IPV among women in poorer households.

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 of Table 2 remain unaltered.

5.2.2. Monsoon rainfall, growing degree days, and extreme degree days

Approximately 70-85% of the annual rainfall is received in the monsoon months of June to October in Bangladesh, and optimal rainfall during this period is critical to the country's agriculture. As an additional robustness check and following Afridi et al. (2022), we construct another measure that captures low monsoon rainfall occurrences specifically. To define a drought shock for a specific year, we calculate the total cluster-specific rainfall for the monsoon months. We then compare this with the long-run monsoon rainfall average (using the 20-year period of 1980-2000). A rainfall shock is defined as 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 growing degree days (GDD) and extreme degree days (EDD) following standard meteorological procedures based on Baskerville and Emin (1969) and Snyder (1985), using a threshold of 32^0C.[31] Our main results are robust to the inclusion of monsoon drought shocks, GDD, and EDD.[32]

5.2.3. Heterogeneous analyses and effects by decade of birth

We conducted a series of analyses evaluating heterogeneity across residency, literacy, economic prosperity, and birth cohorts. Please see Section A.1 and Tables A3 and A4 in the Appendix for details.

5.3. Wealth and agriculture dependency

[31] Kawasaki and Uchida (2016) suggests that depending on the growth stages, the cutoff temperature between growing and harmful degree days is between 31 and 33^0C for rice.
[32] Results available on request.

In this subsection, we examine whether wealth and agriculture dependency compound each other when communities experience drought. In Panels A and B of Table 3, we present results where the samples are partitioned based on both wealth strata and the share of employment in agriculture at the *upazila* 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.[33] We construct indicators measuring the degree of agricultural vulnerability to climate change, and code a variable that takes a value of one 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, decrease in livestock and poultry health, and land availability for agriculture.[34] The indicator is then constructed based on the quartiles of

[33] This report is a publication of this Ministry 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. The assessment spans the entire country, focusing in detail at the *upazila* administrative level.

[34] For instance, for constructing the crop yield vulnerability index, experts focused on four components of exposure: (1) consecutive dry days (2) riverine floods (3) flash floods (4) storm surge height. In assessing vulnerability related to declines in livestock and poultry health, they focused on factors such as humidity, average summer temperatures, and the frequency and duration of heatwaves. For evaluating the vulnerability of land available for agriculture, the assessment considered sea level rise, storms, cyclones, and flash floods. In each instance, various geographic and socioeconomic factors were also considered to reflect potential adaptive capacity. The corresponding data was then normalized, weighted, and aggregated to obtain standardized vulnerability scores for each *upazila*.

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 of dry shocks and the vulnerability index presented in Panel C of Table 3 are all positive and significant. The *p*-values on the null hypothesis that the results are jointly equal to zero indicate that the null is rejected in columns (2) through (4). The total effect of an increase in the number of dry months for women in the lowest wealth quintile 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 fisheries.

5.4. Results focusing on agricultural households

We examine whether intra-family employment structure plays a role, with results presented in Table A5. We focus on households where the husband 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 A5 which focuses on agricultural households, now is.

In Panels C and D, we delve deeper into these households and focus on samples by women's employment status. We find that the results are evident mostly for unemployed women in agricultural households (Panel D). This finding lends support to the hypothesis that more dry periods impact women in agricultural households by increasing the precariousness of total household income, since there is a protective role played by the additional income contributed by working women in Panel C.

To complement our analysis on attitudes towards IPV, we use data from the DHS 2007 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).[35] We find supporting evidence in Table 4, which reports a positive association between the frequency of dry months experienced over the past 3 years and the experience of IPV.[36]

5.5. Other agency indicators

Until now, we have used women's perception of the acceptability of violent behavior to proxy for their status. In Table A6, 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 (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).[37]

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[35] Using only one wave of data constrains statistical power because of reduced sample size. In this case, we use region fixed effects only, while keeping the same set of controls as in equation (1). As a consequence of smaller samples, results for unemployed women, or unemployed women with husbands employed in agriculture, are mostly insignificant.

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

[37] 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

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.

6. Climate resilience investments shield women from IPV

Starting in the 2000s, the Bangladeshi Government implemented several measures directly aimed at mitigating the effects of climate change. These measures were executed as a nationwide initiative to strengthen resilience, diminish vulnerability and bolster adaptive capacities, and denoted as Bangladesh Climate Change Trust initiatives. In this section, we analyze these climate fund projects.

6.1. Bangladesh Climate Change Trust (BCCT) – Background

To support the Climate Change and Action Plan (BCCSAP), the Government of Bangladesh launched the Bangladesh Climate Change Trust (BCCT) in 2008, later revised in 2009.[38] The BCCT is a domestic climate change fund, and its creation symbolizes the government's commitment to building climate resilience 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 agriculture, infrastructure development, research, knowledge creation, 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 by

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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.

[38] 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).

improving disaster response. The BCCT also aims to promote 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 women are most at-risk due to entrenched gender disparities, societal norms, and unequal control over resources.[39]

Most of the projects focus on mitigating the effects of climate change on agriculture. For example, in Kalapara Upazila (Patuakhali District), a BCCT-funded project aims to enhance agricultural productivity and address waterlogging by rehabilitating canals in coastal polders to conserve rainwater. In Daudkandi and Chandina Upazilas (Comilla District), six dams and nine canals were dredged and restored as part of an irrigation and drainage initiative. In other areas, BCCT projects focus on building infrastructure to reduce climate shocks and providing social protection for women and children to strengthen resilience against river erosion, floods, droughts, and other disasters. Some sub-districts benefit from multiple projects during the study period, including initiatives aimed at increasing agricultural yields during crises, managing droughts and floods through community participation, afforestation efforts, and climate-resilient urban development. These projects also foster innovation, such as developing salt-tolerant crops, and provide financial protection to vulnerable populations. They aim to partially offset climate-related revenue losses by implementing gender-responsive climate adaptation strategies.

6.2. Project allocation

[39] The first Climate Change Gender Action Plan (ccGAP), introduced in 2013, reflected the government's dedication to sustainable development and gender inclusion in climate change policies and actions. It was developed by the Ministry of Environment and Forests, with support from Finland and the International Union for Conservation of Nature (IUCN), as part of the BCCSAP. UN Women and the Bangladesh Climate Change Trust (BCCT) have recently collaborated to update the ccGAP. The revision aims to incorporate new gender guidelines to ensure BCCT can effectively plan, implement, monitor, and evaluate gender-responsive climate projects. Additionally, BCCT is enhancing its project planning process to integrate these guidelines, encouraging the development of gender-inclusive climate initiatives across different sectors. Source: *Bangladesh Climate Change Trust and UN Women Bangladesh (2024), Bangladesh Climate Change and Gender Action Plan 2023.*

We digitized the list of approved and finalized projects from the BCCT'S official site on the Bangladesh National Portal.[40] 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* level.

The BCCT project portal (accessed on January 13, 2023) provides regular updates on the status of approximately 300 projects (with 25 projects given the status "funds not issued", and more than 40 projects with the status "Go not issued"). Further, some of these projects lack location and date information due to pending fund releases and approvals, making their implementation uncertain. To ensure the reliability of our dataset, we exclude these projects, focusing instead on agricultural projects with complete information on start and actual or expected end dates. This selection criteria narrows our dataset to 200 projects.[41] In total, we pinpoint the sub-district locations of 183 projects spread throughout Bangladesh with varying start and ending dates spanning 2010 to 2020. Figure A1 shows the *upazilas* (sub-districts) with at least one BCCT project during our study period.

Table A7 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

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

[41] Within this sample, some projects are designated as spanning "all over Bangladesh" to align with national policies and are primarily managed by the Ministry of Environment and Forests, the Ministry of Health and Family Welfare, and the Ministry of Education. For instance, project ID 207, titled "Social protection for women and children living in disaster-prone environments due to climate change," is marked as nationwide. Additionally, seven projects have unspecified locations: three with unreleased funds, two lacking end dates, one conducting a pilot plant study, and another promoting solar technology in the education sector. Furthermore, some projects are only specified at the district level, representing a more aggregated administrative classification.

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 and urbanization, are farther away from urban centers and roads, and closer to the coast. Our empirical design takes all these factors into account, despite the fact that there is also an element of randomness in this aid noted in the literature.[42]

6.3. 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:

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

where sd denotes *upazila* or sub-district, and $BCCTproject_{sd}$ 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 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.[43] Our expectation is that π, the impact of BCCT projects, will exert an attenuating influence on the effect of dry shocks on the outcome variables considered. We are also interested in the net effect of drought

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[42] 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.

[43] 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.

on acceptance of IPV in sub-districts with active BCCT projects, $(\beta + \pi)$. If this net effect is not statistically different from zero, then BCCT projects buffer the negative effects of dry shocks.

To account for potential selection stemming from non-random project allocation, we follow Knutsen et al. (2017), Kotsadam et al. (2018), and Zhang and Huang (2023) and leverage the location and time at which BCCT projects are active. 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 essentially compares only (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 as yet), in order to isolate the effect of the treatment. Our model also includes 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.[44]

6.4. Results

Results are presented in Table A8. We note that the estimated drought impacts, β in equation (3), align with the results in Table 2. The coefficients on the interaction terms are measured with error except in the case of agriculture-dependent communities. We focus on agriculture-dependent communities given this, and report results in Table 5. Coefficients on the interaction terms between drought and BCCT projects, π, are negative and measured precisely in columns (1) and (2), indicating

[44] 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.

that the net effect of dry shocks diminishes considerably with BCCT project implementation.[45] In column (2), we introduce an indicator for the presence of an inactive project and its interaction with dry shocks. Neither of these variables is significant.

We next explore how our effects vary based on the number of active projects. In column (3), we find that the influence of dry shocks is mitigated 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.[46]

Table 6 examines attenuation effects from the presence of climate projects by considering three sub-samples based on wealth quintiles. These results corroborate our previous results and show that the relationship between dry shocks and women's tolerance of IPV decreases markedly in the presence of BCCT projects, especially amongst the poorest agricultural households. Importantly, across all the results presented in Tables 5 and 6, joint significance tests for ($\beta + \pi = 0$) fail to reject the null. That is, BCCT projects mitigate the harmful consequences of dry shocks on women's acceptance of IPV.[47]

6.5. Robustness

We perform a number of robustness checks on the ameliorative effects of BCCT projects. The first check pertains to the sample of respondents in our study. In this regard, we turn to the most vulnerable respondents (in the lowest quintile) and use data on agricultural employment in Table A9. In column (1), we evaluate women whose primary occupation is in the agricultural sector. In column (2),

[45] We test for statistical equivalence of the drought variable and its interaction with BCCT projects. In column (1), the *p*-value is 0.004 indicating that we can reject equivalence. Similarly, in column (2), the *p*-value is 0.005, again indicating that these variables are statistically different.

[46] We observe that the coefficients for active BCCT projects are occasionally positive, albeit with marginal significance. Using equation (3), the net average effect of BCCT is represented by ($\kappa + \pi$). With an average of 5.67 dry months in our sample, the net impact of BCCT on households experiencing average dry shocks is negative but small. Other studies with similar unexpected level effects include Ajefu and Abiona (2020), which examines the mitigating effects of land tenure on drought-induced food insecurity in Malawi, and Garg et al. (2020), which assesses whether NREGA cushions the impact of temperature on test scores in India. Overall, our net results indicate that active BCCT projects effectively buffer losses during drought events.

[47] Although we anticipated partial attenuation of the main adverse impacts, 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.

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 in agriculture. In all cases, BCCT projects moderate the negative effects of dry shocks.

In Panel A of Table A10, 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 including 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; and 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 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 A10, the sign and significance of the interaction terms between dry shocks and BCCT project remain robust.

So far, we have considered projects that were implemented before the survey. Since this could include projects that might have already ended, in Panel B of Table A10, 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 exclude projects that were introduced during the survey year, thus ensuring that we only consider those that have had some time to yield effects. None of these refinements change the original results.

In order to further adjust for possible selection in BCCT sites, we implement 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 A11. The post-matching estimator yields similar but noisier results as compared to our estimates in Tables 2 and 5, potentially because of the reduced sample size.[48] The signs on the interaction terms in Table A11 are consistent with those from before, pointing to BCCT projects moderating drought impacts.[49]

We are able to obtain location data for a majority of BCCT projects, but not all of them. Rustad et al. (2020) notes that such an absence might mean that our control group has also received assistance at some point. This implies a conservative bias for us.

6.6. The potential impact of other development assistance

6.6.1. Development assistance from other donors

Bangladesh has launched other development initiatives and in the absence of controlling for these, we might mis-state the true attenuation afforded by BCCT projects.[50] Our data indicates that about 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 net out other development assistance, 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, UNDP, Islamic Development Bank, and DfID.[51] The dataset traces a total of 299 aid initiatives across 3,641 locations in Bangladesh from 2000 to 2015. Figure A2 illustrates the distribution of all projects throughout Bangladesh based on data from this source.

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[48] We implemented the nearest-neighbor match using individual characteristics primarily because of the possibility of migration. If the relatively wealthier move away from vulnerable areas because they can afford to, then results based on climate match characteristics, 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. The set of individual characteristics include age of the women and her spouse, religion, rural residency, and age of the first child.

[49] In a study that post-dates us, Eskander and Mahmud (2024) consider the buffering impacts of this trust fund on rainfall shocks to child health employing balance tests primarily to correct for non-random program placement.

[50] 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.

[51] 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.*

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.[52] Following Kotsadam et al. (2018), we limit our analysis to projects with precise geocodes and with information on when they were established and completed. With these restrictions, we have projects in 1,861 locations. 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, and include in the empirical design of equation (3).

The results are presented in Table A12. As seen in Panel A, the coefficients for the new interaction terms are negative, but significant only in columns (1) and (4) for women in the three lowest wealth quintiles. The interaction terms for BCCT projects remain negative and significant as before. Panel B demonstrates that the attenuation impact of BCCT projects remains when we condition on the number of other development projects that are within 10 km. Results in Table A12 provide suggestive evidence that BCCT projects better shield women from climate-related shocks as compared to other more general-purpose development projects.

6.6.2. Bangladesh climate change resilience fund

We also note the establishment of the Bangladesh Climate Change Resilience Fund (BCCRF) by the government in 2010, another program simultaneously implemented during our study period.[53] The project ended in 2016 due to differences between donors, the World Bank, and the Bangladeshi government.[54] Relying on official BCCRF annual reports prepared by the World Bank, we obtain

[52]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.

[53] The BCCRF was owned and managed by the Ministry of Environment and Forests, with a governance structure that included a Government Council and a Management Committee. The World Bank monitored the transparency and accountability of the BCCRF's operations.

[54] 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.

information from 2011 through 2016. Table A13 provides details on each of the five investment projects under the BCCRF initiative 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. We then re-estimate our baseline model but exclude respondents in areas that benefited from multiple types of projects.[55] Results in Table A14 show that our results remain.

In summary, the checks we implement in order to ascertain the robustness of results from BCCT projects include controlling for all pre-determined location-specific and socio-economic covariates, leveraging differences between projects currently active and those selected for the future but not active as yet where this timing difference is likely random, netting out projects that were active in the past but are not currently so, or became active just in the year of the survey, methodologies such as nearest-neighbor matching, and conditioning on the presence of other development projects in the sub-district.

6.7. Potential mechanisms

We next examine why BCCT projects may better shield women from the deleterious impacts of drought, especially in agricultural-dependent communities. Several mechanisms may be at work. BCCT could facilitate agricultural adaptation and resilience when facing droughts, provide direct income support in the case of disasters or during times of food insecurity, and improve women's agency and access to information through institutional and capacity-building programs.

Here we offer evidence on these factors. We first test whether BCCT projects may protect agricultural activities against droughts, especially rainfed agriculture which is prone to climate risks. To do so, we assemble a panel dataset ranging from 2000 to 2018 that takes each DHS cluster as a spatial unit, paired with additional remotely sensed gridded datasets that proxy agricultural land use, crop yield,

[55] We follow this strategy since we know the location of BCCRF projects primarily at the district level. Hence it is difficult to identify effects of these programs since we include district fixed-effects in our models.

and local economic conditions. Specifically, we measure land use decisions using high-resolution (300m) Copernicus Land Monitoring Service (CLMS), which allows us to distinguish rainfed agriculture from irrigated agriculture and other land uses.[56] The two outcome variables are the percentage of land allocated to rainfed and irrigated agriculture within 10km of each DHS cluster. We measure crop yield by using normalized difference vegetation index (NDVI), available at a monthly interval with a spatial resolution of 1 km. NDVI has been widely used to predict and forecast *aman* (monsoon) season rainfed rice in Bangladesh (e.g., Faisal et al. 2019, Shew and Ghosh, 2019, Islam et al. 2021, Mamun et al. 2021). Here we construct *aman* season yield proxies by taking the difference in NDVI metrics between the end of the season (October) and the start of the season (July), which allows us to difference out components of NDVI that experience minimal changes within each growing season.

To shed light on potential mechanisms, we estimate regressions similar to that of equation (3), replacing the outcome variable with the local agricultural outcomes, and include the number of hot and wet months, *aman* season growing degree days (8-32°C) and extreme degree days (>32°C), and district by year fixed effects (Schlenker and Roberts, 2009, Lobell et al. 2013). Results are presented in Table 7. We find that consistent with the literature (Ji and Cobourn 2021, He and Chen 2022), drought affects multiple margins of rainfed agricultural production: Drought reduces the percentage of land occupied by rainfed crops (column 1) and decreases yield during the rainfed *aman* season, measured by NDVI differences (column 5). BCCT projects attenuate the negative impacts on rainfed crop acreage (column 2) and crop yield (column 6), as the interaction terms between drought and having BCCT projects are positive and statistically significant. That is, BCCT projects provide resilience by protecting cropland dedicated to rainfed crops and by shielding yield losses. For irrigated agriculture, we find that dry shocks decrease land allocated to irrigated crops (column 3); there are mitigation effects in column (4).

[56] The land use product is with ESA-CCI LC project's land cover map from 1992-2015 (Defourny et al. 2017).

In addition to affecting agriculture, we also seek to evaluate how BCCT projects influence other measures that may be explanatory. Table A15 presents results on the impacts of BCCT projects on outcomes that are related to women's agency through improved access to information, enhanced financial opportunities, increased welfare, and greater awareness. We find that 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. These effects are generally more pronounced among the two lowest wealth quintiles or the lowest wealth quintile.

6.8. Discussion

The evidence thus far 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 in moderating the impact of income shocks on domestic violence, reveals that the adverse effects of dry shocks 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.

In keeping with the above, 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 reduce income risks which, in turn, facilitates women's social protection. Further, our finding that

BCCT projects bring relatively more moderating influences than other types of development assistance suggests a need for more targeted interventions in such contexts.

7. Conclusion

This paper provides evidence on the intersection of climate change, intimate partner violence, and climate resilience initiatives in Bangladesh. By leveraging a novel dataset that links detailed earth observation remote-sensed meteorological and other data with a comprehensive set of indicators of women's agency in the Bangladesh Demographic and Health Surveys, we demonstrate the significant impact of climate shocks on dynamics in vulnerable communities. Our findings reveal that dry shocks exacerbate the acceptance and experience of IPV among women, particularly those in poor and agriculture-dependent households. These results underscore the critical interaction between environmental stressors and entrenched socio-economic risk factors, highlighting how climate-induced disruptions may deepen existing inequalities.

Importantly, our study additionally identifies the mitigating influences of climate resilience initiatives funded by the Bangladesh Climate Change Trust. These projects effectively counteract the adverse impacts of droughts, especially in communities that are particularly susceptible to environmental insults. Our analyses show that the presence of BCCT projects nullifies the detrimental effects of dry shocks, indicating that targeted climate resilience interventions may play a crucial role in protecting women from the harmful consequences of climate change. Agriculture serves as an important theatre. We find that BCCT projects reduce agricultural losses in the face of recent droughts. BCCT projects also improve women's access to information, cash earnings, and mobility. The protective effects suggest that social norms may be amenable to change in the relative short-run, which is contrary to the widely held perception that they are enduring and difficult to revise. We aim to pursue this question in future work with data from more countries in order to understand how climate may shape long-standing cultural and social conscripts, and whether such changes may have inter-generational consequences.

Our results have important policy implications. They underscore the necessity for integrated climate policies that not only address environmental sustainability and disaster resilience but also promote gender equity and the protection of vulnerable populations. Specifically, our results advocate for targeted gender-sensitive climate resilience projects, particularly for agriculture-dependent and low-income groups, as those projects are found to have measurable positive spillover effects that safeguard women's well-being in the face of increasing climate shocks. Our results add to the literature that notes that women are disproportionately affected by climate change, hence providing women with greater access to financial resources and improving their awareness and mobility such that they may participate in economic realms more meaningfully, may serve to enhance their resilience to climate shocks.

The escalating challenges posed by a changing climate in less prosperous nations underscore the urgent need for comprehensive and careful research on impacts and interventions. As climate variability intensifies, its socio-economic impacts are likely to express along pre-existing social, economic, and cultural fault-lines. Our paper contributes by providing evidence on the intersection of climate shocks and women's agency, demonstrating the disproportionate effects of widespread environmental stressors. By evaluating the ameliorative effects of domestically-funded initiatives, our research offers hopeful insights into effective policy interventions that may serve to protect at-risk groups, thereby fostering resilience and equity in the face of ongoing climate crises.

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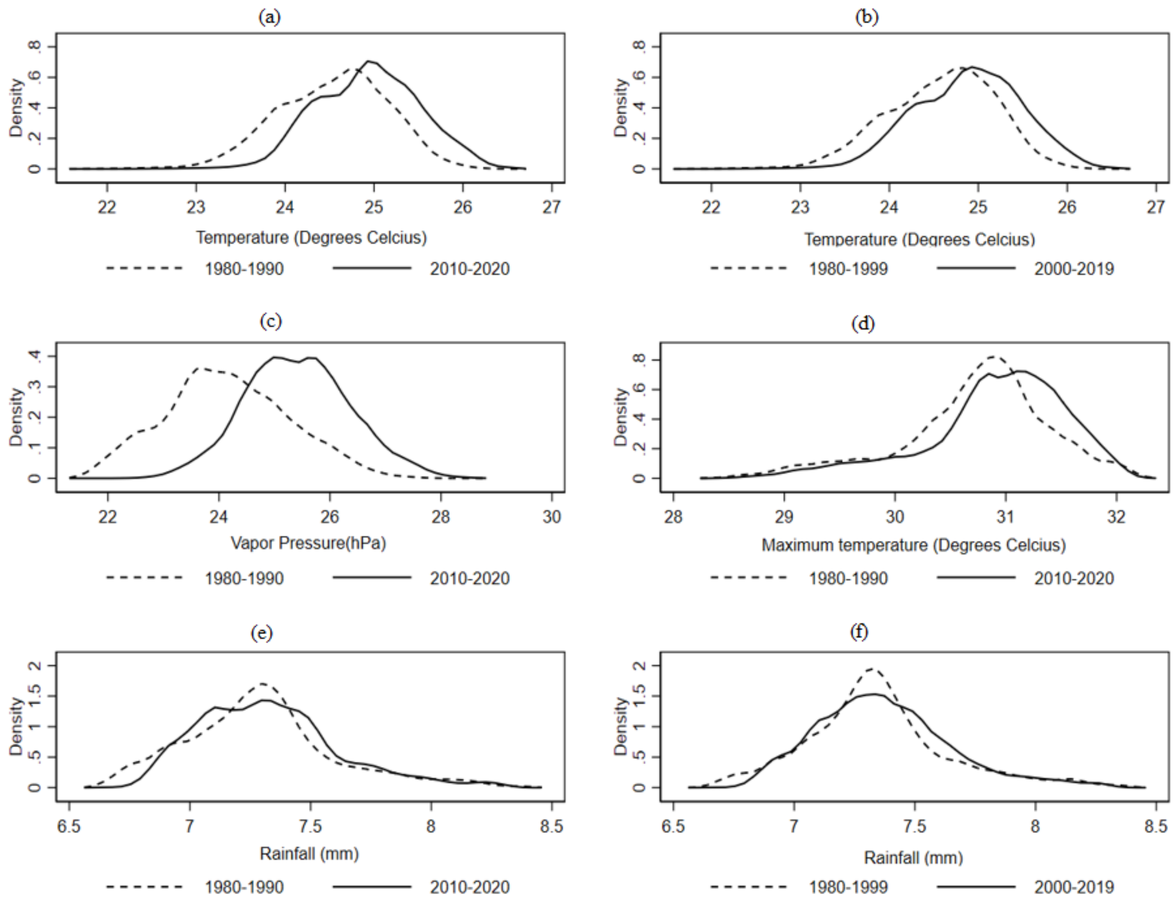
Figure 1: Location of BDHS clusters

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). On average, each district contained 10 clusters, with a maximum of 37 clusters across the three DHS waves 2011, 2014, and 2017. At the subdistrict level, there was an average of 2 clusters, with a maximum of 11 clusters over the three years.

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	Std. Dev
Panel A: Agency indicators		
Attitudes towards DV	0.268	0.443
(=1 if she agrees with at least one of the five statements that justify wife-beating)		
Participates in no decision	0.168	0.374
(=1 if she reports not participating in decisions regarding her own healthcare, major household purchases, visits to her family or relatives, and child healthcare)		
Decision index	0.671	0.392
(An average of responses related to decisions pertaining to her own healthcare, major household purchases, visits to her family or relatives)		
Freedom of movement	0.670	0.470
(=1 if she has the freedom to visit the health center alone or with her children)		
Control over own earnings	0.576	0.494
(=1 if she received cash earnings in the past 12 months and makes joint decisions on how to use her earnings with her husband)		
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
(below 1 SD of historical average rainfall)		
Number of wet months	4.420	1.734
(above 1 SD of historical average rainfall)		
Number of hot months	17.423	3.252
(above 1 SD of historical average temperature)		
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. Please see the text for further details. 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 as detailed in the text.

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
Mean of dependent variable	0.268	0.289	0.247	0.306	0.321	0.333
Individual and household controls	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓
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 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: 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 number of dry months (past 3 yrs)	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 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 4: 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 5: 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:				
No. of dry months + (No. of dry months x BCCT) = 0	-0.007	0.008	-0.005	-0.005
F-statistic	0.840	0.920	0.420	0.540
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 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 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 6: 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)
	0.062*	0.077*	0.038	0.080	0.061*	0.075*	0.037	0.076
BCCT project (active before survey)	(0.036)	(0.040)	(0.046)	(0.074)	(0.036)	(0.040)	(0.046)	(0.074)
	-0.018**	-0.020**	-0.020**	-0.035**	-0.018**	-0.020**	-0.020**	-0.035**
Number of dry months x BCCT project	(0.008)	(0.008)	(0.010)	(0.014)	(0.008)	(0.008)	(0.010)	(0.014)
					-0.011	-0.034	-0.034	-0.094*
Inactive BCCT project (active after survey)					(0.037)	(0.041)	(0.048)	(0.055)
					0.002	0.005	0.005	0.012
No. of dry months x inactive BCCT project					(0.005)	(0.006)	(0.007)	(0.009)
Joint test: No. of dry months + (No. 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 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 two lowest wealth quintiles. Columns (4) and (8) report results from subsamples for agricultural-dependent communities and in the lowest wealth quintile. 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 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 7: The Effects of BCCT Projects on Mitigating Agricultural Impacts of Drought Shocks

	Dependent Variable					
	% Rainfed crop		% Irrigated crop		*Aman* (rainfed) season NDVI	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Number of dry months (past 3 years) (below 1 SD of historical average rainfall)	-0.004*	-0.004**	-0.010***	-0.010***	-0.004*	-0.005**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Active BCCT project		-0.005		-0.015		-0.049***
		(0.012)		(0.020)		(0.019)
Number of dry months (past 3 years) x Active BCCT project		0.005*		-0.002		0.010**
		(0.003)		(0.004)		(0.004)
Degree Days	✓	✓	✓	✓	✓	✓
Heat and wet months	✓	✓	✓	✓	✓	✓
District x Year Fixed Effect	✓	✓	✓	✓	✓	✓
Observations	17,214	17,214	17,214	17,214	17,214	17,214
R-squared	0.641	0.641	0.732	0.732	0.335	0.335

Notes: The regression runs on sample of a cluster by year panel, from 2000-2018, on DHS cluster locations in the 2011, 2014, and 2017 DHS waves. The sample is restricted to agriculture-dependent clusters. The outcome variables are the percentage of land allocated to rainfed crops within 10 km of the cluster location (column 1 and 2); the percentage of land allocated to irrigated crops within 10 km of the cluster location (column 3 and 4); and differences in NDVI between the starting and the ending month of the Aman season (October minus July, column 5 and 6). *Active BCCT project* is a dummy variable that is equal to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented in the current year. All regressions include district by year fixed effects. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1

Appendix

Section A.1 Heterogeneous analyses and effects by decade of birth

In Table A3, we perform heterogeneity analyses for the lowest wealth quintile of households.[57] We select three 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.

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. We find that the main effects indeed vary with literacy status; the effect is evident among illiterate respondents only.

Finally, we check whether effects vary across levels of economic prosperity. These results shed light on a potential mechanism; the reduction in women's agency may be due to decreases in economic activity. We use satellite data on cluster-specific nighttime light intensity in the survey year as a measure of 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. Columns (5) and (6) show that there is a detrimental impact of dry months in less prosperous clusters only.

Effects by decade of birth

We next consider heterogeneity by cohorts. We augment equation (1) with indicators for women's birth decades and include separate interaction terms for the frequency of dry months and

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

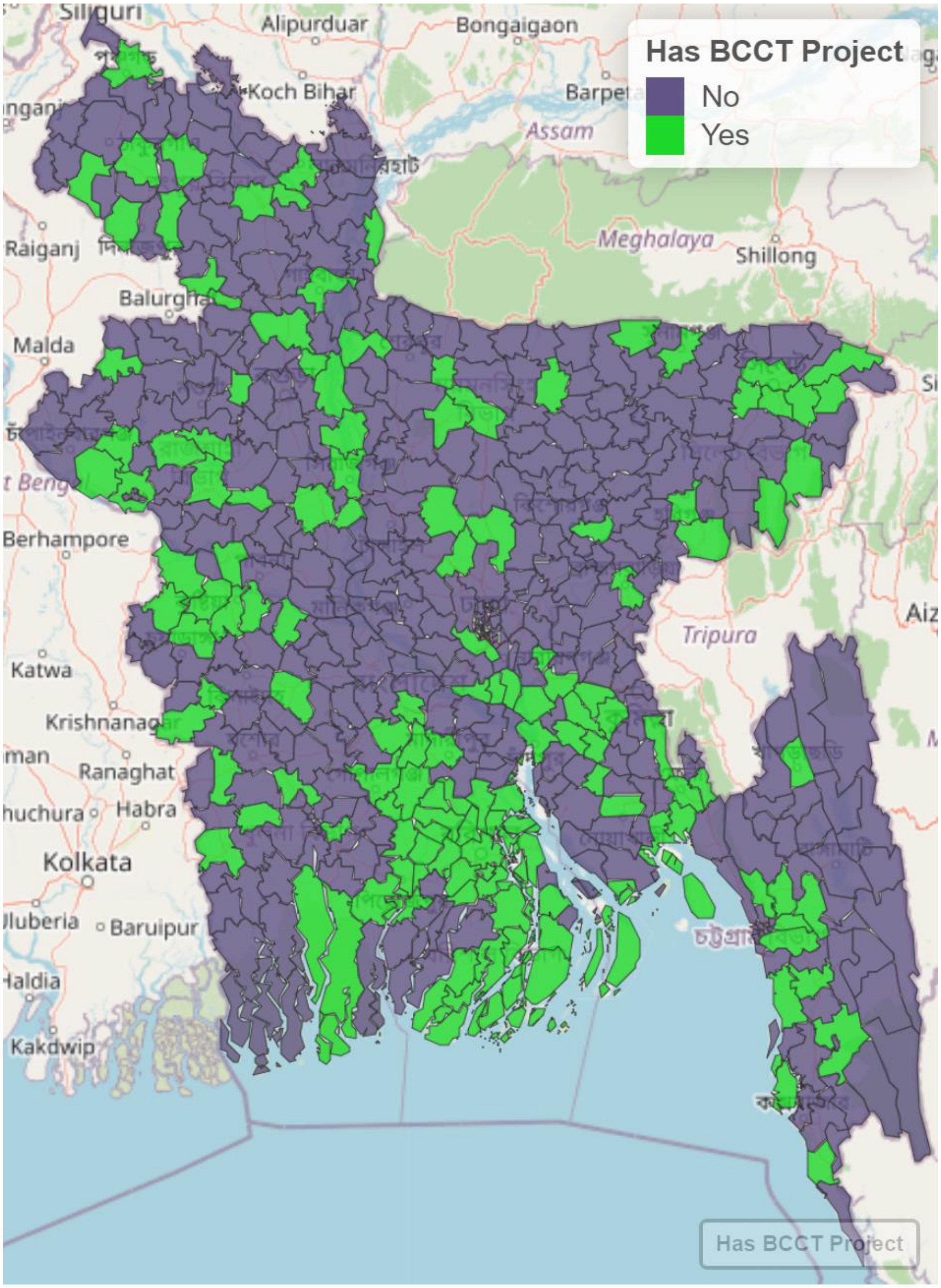
each birth cohort. The interaction terms are thus $numdrymths_{cdmt_{-36}} \times cohort_b$, $numwetmths_{cdmt_{-36}} \times cohort_b$ and $numhotmths_{cdmt_{-36}} \times cohort_b$. We report the net effect of droughts for each cohort with associated p-values in square brackets in Table A4.

We find that while women's acceptability of IPV across all birth decades is 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 is larger in magnitude as 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.

With greater access to education, digital technologies, and supportive networks, we would, *a priori*, expect smaller impacts for younger women. The effects presented in this section do not support this. Factors that may by explanatory include the increasing frequency and severity of climate shocks in more recent years, as well as traditional gender roles that link age to social standing which place younger women at a relative disadvantage.[58]

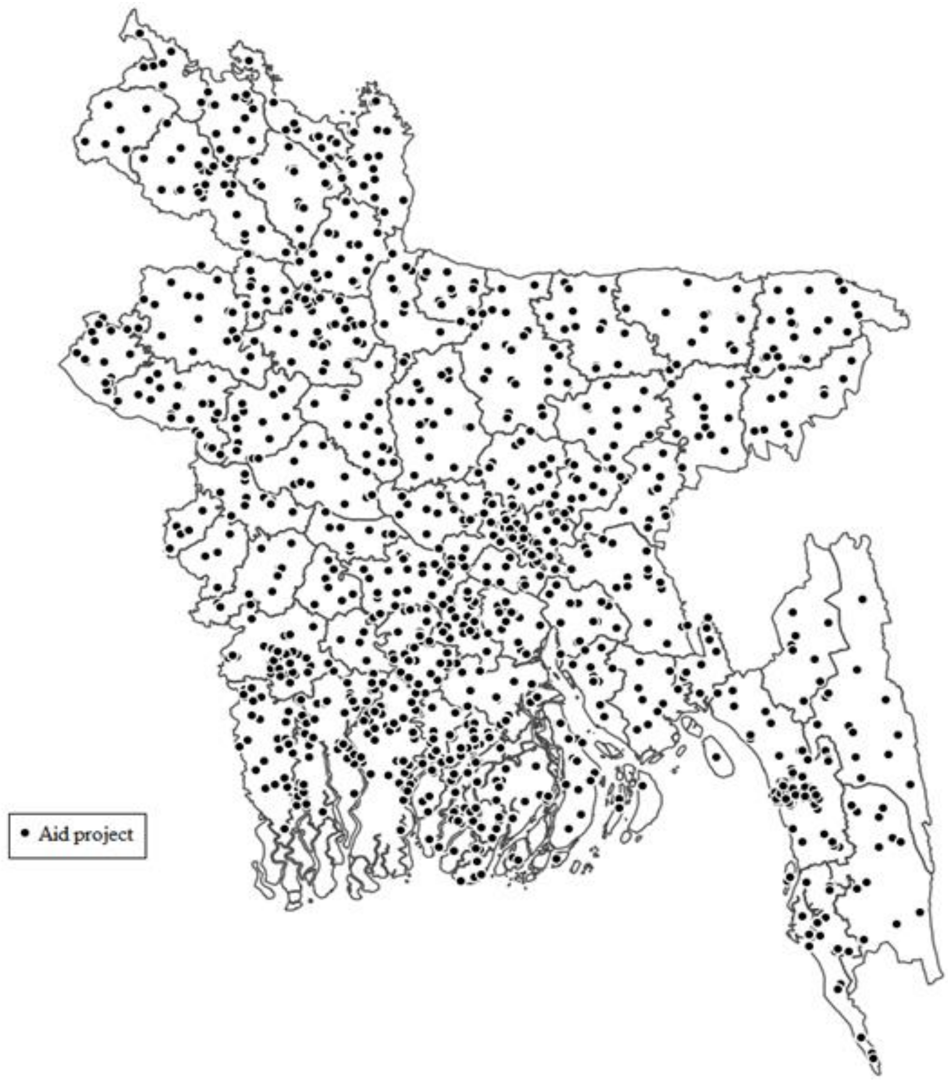
[58] This is consistent with Guimbeau et al. (2023), which also found that younger women are more susceptible.

Figure A1: The sub-districts in Bangladesh with BCCT projects



Notes: Figure A1, constructed by the authors, shows sub-districts that contain at least one BCCT project for our study period. We focus on approved and finalized projects from the BCCT's official site on the Bangladesh National Portal. See text for further details.

Figure A2: The location of aid projects in Bangladesh, 2000-2015



Notes: Figure A2, 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: Robustness checks

	Dependent Variable: Justifies IPV for at least one reason					
	Sample restricted to:					
	Full Sample	Agriculture-Dependent Communities	Non-Agriculture-Dependent Communities	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Alternative functional forms						
Number of dry months	0.028	0.064**	-0.087	0.048*	0.068**	0.115***
(past 3 years, in logs)	(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: Control for residence						
Number of dry months	0.018**	0.033***	-0.014	0.020**	0.024**	0.038***
(past 3 years)	(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: Discretize dry months						
Number of dry months	0.035**	0.027*	-0.015	0.049***	0.045**	0.065**
(past 3 years, 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***
(past 3 years, 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***
(past 3 years, 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
Panel D: Distributional lags						
Number of dry months	0.012	0.011	-0.006	0.015*	0.023**	0.022
(past 12 months)	(0.008)	(0.009)	(0.016)	(0.009)	(0.010)	(0.014)
Number of dry months	-0.012*	-0.008	-0.014	-0.008	-0.014	-0.004
(13-24 months ago)	(0.007)	(0.009)	(0.014)	(0.009)	(0.010)	(0.014)
Number of dry months	0.016**	0.024***	0.009	0.018**	0.021**	0.034**
(25-36 months ago)	(0.007)	(0.009)	(0.013)	(0.008)	(0.010)	(0.014)
Observations	47,885	23,108	22,608	27,085	17,703	8,657

	(1)	(2)	(3)	(4)	(5)	(6)
R-squared	0.111	0.118	0.121	0.113	0.132	0.158
Panel E: Alternative drought measures						
SPEI * **1**(SPEI<=0, dry & hot)	-0.040	-0.028	-0.065	-0.071**	-0.085*	-0.109**
(3-year time scale)	(0.033)	(0.036)	(0.061)	(0.034)	(0.043)	(0.055)
SPEI * **1**(SPEI>0, wet & cold)	0.005	0.040	0.055	-0.031	-0.000	-0.038
(3-year time scale)	(0.054)	(0.051)	(0.128)	(0.061)	(0.062)	(0.076)
Observations	47,885	23,108	22,608	27,085	17,703	8,657
R-squared	0.110	0.117	0.120	0.112	0.131	0.156

Notes: The table shows the coefficients of the variables for climate shocks. 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. 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. Panel A replaces the number of dry, wet, and hot months with their logarithmic forms. Panel B adds women's years of residence as a control variable. Panel C discretizes the number of dry months into four quartiles. Panel D separates the impact of dry months into three windows: within the past 12 months, 13-24 months, and 25-36 months. Panel E uses the Standardized Precipitation Evapotranspiration Index (SPEI) as an alternative measure to drought/hot and wet/hot conditions. 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 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: 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 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 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, 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) (below 1 SD of historical average rainfall)	0.001	0.005	-0.009	-0.015	-0.031	-0.068**
	(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 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 A5: 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 (husband in agriculture)				
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 (husband not in agriculture)				
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 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 A6: The effects of climate shocks on other agency indicators

Sample restricted to: Agricultural households in the lowest quintile

	Dependent variable:			
	No participation in decision-making	Decision-making index	freedom of movement	control over earnings
	(1)	(2)	(3)	(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 A7: 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					
Nightlights (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 A8: 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)	0.005	0.011**	-0.009	0.009*	0.011**	0.017**
(below 1 SD of historical average rainfall)	(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)
	-0.002	-0.018**	0.017	-0.001	-0.002	-0.005
Number of dry months x BCCT project	(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 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 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 A9: 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 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 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 A10: 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 started 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 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 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 A11: 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 A12: Climate shocks, attitudes towards IPV and aid projects: BCCT and Other Development Assistance

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 dev. 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 Number 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 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, and that was still active at the time of the survey. '*Other development projects*' is a dummy variable that equals 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 A13: 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 A14: 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:			
No. of dry months + (No. 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 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. 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 A15: 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 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 one if there was an ongoing development assistance project within 10 km of the respondent's cluster. Access to media equals 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.