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

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Abstract

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 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, primarily by eroding women's outside options. 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 generating positive spillover effects that ameliorate the negative impacts of changing climate. We show that these projects enhance resilience in agriculture by reducing the effects of droughts on acreage and yield in rainfed areas, and by bolstering measures of women's agency. Our findings underline the crucial role of targeted policies in fostering climate adaptation and wellbeing.

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

JEL Codes: Q54; J16; O13

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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 to worsen underlying gender inequalities. This unequal burden is further amplified by women's 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 their susceptibility to gender-based violence. Addressing this question using an economics lens is the primary topic of this paper.

Prior work suggests that economic shocks and policy interventions affect intimate partner violence through multiple pathways, including changes in women's relative bargaining power and outside options, as well as through household stress and economic insecurity. Experimental evidence shows that alleviating such constraints through cash and in-kind transfers substantially reduces IPV (Hidrobo et al. 2016; Haushofer et al. 2019), but increases in women's economic activity may also trigger backlash when baseline bargaining power is low (Heath 2014). Despite this understanding, the gender-differentiated impacts of climate change remain a relatively understudied area in the economics literature. For instance, a comprehensive meta-analysis by Burke et al. (2024) found that of 129 climate-conflict studies as of then, only seven focused on gender-based violence, with just one based outside the developed world (Sekhri and Storeygard 2014).

In response to the escalating climate threats, the international community has mobilized significant financial resources to support adaptation and resilience in developing nations. A landmark commitment from the 2009 Copenhagen Accord was the goal for developed countries to provide $100 billion per year in climate finance by 2020. This target was surpassed in 2022, with total climate finance for developing countries reaching over $115 billion.[1] The justification for these sizeable investments is that building local resilience can prevent severe social costs such as forced migration, the loss of livelihoods, and social unrest. Yet, while a growing body of work has evaluated solutions from direct household adaptation (Barreca 2016; Burke and Emerick 2016) to the role of economic assistance programs such as cash transfers (Macours et al. 2022) and credit access (Burgess et al. 2017; Lane 2024), the effectiveness and social spillovers of large-scale, *climate-specific* programs remain largely unexamined.

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 (IPV is thus the main outcome of interest). As is widely accepted, these attitudes may be viewed as measures of social norms (Jayachandran 2015), while also potentially reflecting adaptive responses to economic vulnerability and constrained choices in contexts of prolonged duress and limited exit options (Frezza 2025). Our empirical analyses focus on Bangladesh, a developing country that is amongst the most susceptible to a 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. Concurrently, the incidence of

[1] Statistica, Climate finance worldwide in 2021 and 2022, by source. https://www.statista.com/statistics/1448911/global-climate-finance-by-source/

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), and over one-third of men aged between 15-49 agree that wife-beating is justified for several reasons according to the DHS (NIPORT 2009). Our research thus aims to unravel the nuanced effects of climate-induced risks for women in an environment that is especially 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. These initiatives included a wide range of activities from infrastructural improvements like rehabilitating irrigation canals and river embankments, promoting sustainable agriculture with stress-tolerant seed varieties, to enhancing disaster preparedness and housing resilience. Our study evaluates how effective these BCCT projects are at attenuating the harmful impacts of climate shocks on IPV, and examines mechanisms that lead to their effectiveness. By evaluating how BCCT projects mitigate the relationship between droughts and IPV-related outcomes, we assess whether relaxing economic constraints and improving women's fallback options can buffer the adverse gendered consequences of climate shocks. To the best of our knowledge, ours is the earliest paper to empirically evaluate the effects of nationally-led climate-specific 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 tolerance, experience of IPV, and women's agency. We obtain geo-referenced monthly meteorological data at a spatial resolution of 0.1°

x 0.1° spanning 1980-2020. 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 (SD) below the historical monthly average from 1980-2000. The magnitude of this shock is consistent with other recent studies such as Abiona and Foureaux-Koppensteiner (2018). We construct similar intensity variables for months of wet spells (when rainfall is at least one SD higher than the cluster-specific historical mean) and for months of heat waves (when temperatures are at least one SD higher than the cluster-specific historical mean). We 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, which is strongly correlated with experience of IPV, as noted in Uthman et al. (2011), Titilayo et al. (2014), and Bengesai and Khan (2023). Examining effects more closely, most 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 corresponding increase is 2.5 percentage points. Our results withstand a battery of robustness checks, and we implement heterogeneity analyses to reveal that droughts have

larger negative impacts on the poorest women in agriculture-dependent communities. We also present evidence on the mechanisms underlying these effects. Our results provide less support for stress or backlash explanations, as the impact of droughts on IPV tolerance does not systematically vary with a common stress- or identity-based proxy measure, local male unemployment. Instead, the evidence points to a bargaining mechanism, as the increase in IPV tolerance following drought exposure is significantly larger among women with lower bargaining power measured by limited participation in household decision-making and lack of control over earnings.

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 the timing of initiation and ending of these projects. Our results indicate that proximity to a BCCT project almost completely counteracts the effect of droughts in agricultural communities, and across several wealth strata. The attenuation effects remain even after we control for a host of pre-treatment covariates, and employ a wide variety of tests to control for possible endogeneity in project location. In particular, placebo tests find no significant attenuation effects for inactive (past or future) BCCT projects, and 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, during drought shocks. More specifically, proximity to BCCT projects buffers the negative impacts of drought on an *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 bolstering women's agency through improving access to cash earnings, media, transport facilities, and electricity.

Our paper makes several contributions. 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 (Burke et al. 2015, 2024; Hsiang et al. 2013; Maconga 2023; Ubilava et al. 2022). Importantly, we add to the limited group of studies that analyze gender-based violence (Mannell et al. 2024; Sanz-Barbero et al. 2018; Ranson 2014; Takahashi 2017), especially in developing country contexts (Bollman et al. 2025; Cools et al. 2020; Díaz and Saldarriaga 2023; Nguyen 2024; Sekhri and Storeygard 2014; Sekhri and Hossain 2023). 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 social and economic divides.

Secondly, our work contributes to the policy debate on climate adaptation by providing one of the first empirical evaluations of the *social spillovers* of a targeted, government-led climate resilience program. A growing body of work has studied mechanisms to mitigate climate impacts including direct household adaptation such as adopting air conditioning (Barreca et al. 2016; Randazzo et al. 2023) or switching crops (Burke and Emerick 2016; Cui and Zhong 2024; Li 2023; Wang et al. 2024), the provision of broader economic assistance like cash transfers (Banerjee and Maharaj 2020; Garg et al. 2020, 2025; Hirvonen et al. 2023; Macours et al. 2022; Premand and Stoeffler 2022; Rustad et al. 2020), improved credit access (Burgess et al. 2017; Lane 2024), and subsidized risk sharing (Mobarak and Rosenzweig 2013, Karlan et al. 2014), as well as spillover effects from social policies such as gun and substance control (Colmer and Doleac 2025, Pavanello and Zappala 2025) and access to healthcare (Cohen and Dechezleprêtre 2017; Evans et al. 2024; Mullins and White 2020). Our study complements

this literature by assessing a different and increasingly important class of interventions: Directed climate finance initiatives. We find that the Bangladesh Climate Change Trust (BCCT), a program designed primarily to build agricultural and infrastructural resilience, mostly nullifies the adverse effect of droughts on IPV. This finding demonstrates that targeted climate programs can generate significant positive co-benefits for women's safety and agency, a crucial insight for policymakers involved in designing and justifying the costs of such investments.

Finally, our work builds on the literature on gender equality and women's agency in the developing world, especially on effective ways to limit IPV. 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).

While our evidence aligns more closely with a bargaining-based interpretation – whereby climate shocks weaken women's fallback positions in agriculture-dependent and asset-poor settings – we should note that we cannot definitively rule out the concomitant role of stress- and backlash-related mechanisms as our data are not detailed enough. Further, our results indicate that climate resilience investments can influence women's acceptance of IPV by altering the economic and social conditions under which attitudes toward violence are formed and expressed. These changes may reflect shifts in norm-relevant attitudes, adaptive responses, or a combination of both. Our data also do not allow us to fully disentangle belief change from coping responses, but both are important from the view of understanding how policy may mitigate violence against women. Our findings also suggest that social norms on acceptance of IPV may be amenable to change in relatively short periods of time, particularly when women's agency is instrumental. This leads to questions about the widespread beliefs that acceptable cultural and social "rules" of behavior for women are "sticky" and long-standing. This is a

hopeful result, with current and inter-generational consequences that we hope to investigate further in future work.

2. Conceptual details and measurement

2.1. Climate shocks and IPV

Climate shocks can influence intimate partner violence (IPV) through clear channels that have been noted previously. These include increased stress due to men losing jobs and subsequent income strain experienced within the household, decreased bargaining power as women lose outside options as their activities may be particularly vulnerable to unexpected changes in weather, and backlash effects where women's take-up of additional coping work to stabilize household income is viewed unfavorably and as a threat by male partners. We analyze each of these channels systematically and in detail below; however, in this section, we elaborate on these channels interchangeably and provide general theoretical underpinnings for why climate shocks might affect IPV using broader concepts of changes in household resources, challenges to traditional gender norms, and shifts in intra-household bargaining power.[2]

Environmental disruptions often produce abrupt income losses and uncertainty, especially in agrarian settings where livelihoods depend on rainfall and seasonal productivity. These shocks can strain household relationships, alter traditional gender roles, and heighten stress within families, with important implications for IPV. This is particularly relevant in vulnerable communities where women have limited fallback options, and where cultural and institutional conditions may allow violence to be more widely tolerated (Benson et al. 2013).[3] The broader literature shows that climate variability affects socio-economic structures in ways that can influence women's well-being and autonomy, which

[2] Not all effects need to be negative, however. Recent 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).

[3] In such poorer communities, the communal backdrop can further impact the climate-IPV nexus due to weaker institutions.

provides a foundation for examining how climate shocks relate to IPV. Extreme weather events place additional pressure on households that lack access to savings, safety nets, or alternative sources of support. Climate shocks during key agricultural periods are associated with pronounced income declines that disproportionately affect rural populations. When livelihoods deteriorate, women can become more exposed to IPV through both direct and indirect channels. The increased vulnerability affects 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 (Diaz and Saldarriaga 2023).[4]

A growing body of research links climate shocks to IPV incidence. For instance, Abiona and Foureaux-Koppensteiner (2018) find that droughts lead to an increase in IPV in Tanzania. In rural areas of the Peruvian Andes, Diaz and Saldarriaga (2023) report that a woman's experiences of IPV increase 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 link negative rainfall shocks to higher IPV rates among adolescent girls. Recent additional evidence highlights temperature as another important pathway: Rizzotto et al. (2025) find that higher daily maximum temperatures significantly increase domestic violence in Brazil. These studies provide robust evidence that climate-related income and production shocks can raise IPV prevalence. For these reasons, we focus on IPV as the main outcome in this study.

Social norms can influence how climate shocks translate into IPV. Gender-biased structures that assign domestic and caregiving responsibilities primarily to women limit their access to stable

[4] 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).

employment, reduce their ability to diversify income sources, and restrict their capacity to respond to environmental risks (Afridi et al. 2022; Escalante and Maisonnave 2022; FAO 2024).[5] These constraints are reinforced during climate shocks, when declines in female employment and earnings reduce women's financial independence and bargaining power. In contexts with limited community support and restricted access to welfare services, often financial hardships and diminished employment opportunities combine to undermine women's ability to avoid abusive situations (Farmer and Tiefenthaler 1997). Norms that govern marriage and household formation may also be affected by environmental stress; for example, droughts have been shown to increase the likelihood of early marriage (Corno et al. 2020), with important implications for women's exposure to IPV.

We note that the link between climate shocks and IPV is likely influenced by relative shifts in household dynamics, as men may also be affected. This interdependency underlies the emphasis on changes in women's resources relative to men's in household bargaining frameworks. A 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. Additionally, if climate change disproportionately affects men's employment, it may prompt an increase in aggressive behavior due to increased stress. Alternatively, if women take on additional work in these circumstances to support household income, violence may emerge when men confront threats to their identity or are forced into non-traditional roles (status inconsistency), with resulting backlash consistent with household bargaining theories (Aizer 2010; Bobonis et al. 2013; Bloch and Rao 2002; Eswaran and Malhotra

[5] 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 such as childcare.

2011; Hidrobo and Fernald 2013; Hornung et al. 1981; Pollak 2005; Tauchen et al. 1991). In such contexts, relative economic changes may influence both IPV tolerance and IPV experience, as we discuss below.

2.2. IPV attitudes and relationship to IPV experience

The only geocoded round of the Bangladesh DHS that collects information on experience of IPV is from 2007. While we do evaluate these data in detail and present results below, since IPV experience is not collected consistently across survey waves, we use information on women's attitudes towards IPV, which is collected across multiple rounds, as an indicator of IPV experience. We justify why acceptance of IPV is a good proxy for actual IPV experience based on existing research next.

Research on South Asia suggests that attitudes toward wife beating may be more easily disclosed than personal experiences of violence. Rani and Bonu (2009) note that respondents may be more willing to express approval or disapproval of IPV than to report victimization, which makes attitude data informative about underlying IPV patterns. Bangladesh-specific evidence demonstrates that IPV risk reflects the broader normative environment. Women living in communities with higher autonomy and fewer constraints on mobility or decision-making face lower risks of IPV, suggesting that community norms shape both vulnerability and behavioral outcomes (Koenig et al. 2003).

Several studies document a positive association between IPV-tolerant attitudes and the experience of violence. Uthman et al. (2011) show that women who justify wife-beating are more likely to report spousal abuse. Titilayo et al. (2014) also find that tolerant attitudes are associated with higher IPV incidence. Bengesai and Khan (2023), drawing on data from Malawi, Zambia, and Zimbabwe, show that IPV risk doubles when both partners condone wife-beating. Additional support comes from rural Niger where Shakya et al. (2022) find that women who report IPV are more likely to endorse attitudes justifying violence, and that men's perceptions of community acceptance of IPV are strongly

related to IPV perpetration. The results of these studies strongly indicate that attitudes toward IPV are important markers of experience of violence.

Recent evidence provides further insights into the relationship between attitudes and lived experience. Frezza (2025) examines how exposure to IPV affects tolerance of violence, exploiting variation in the minimum legal drinking age in India that led to increased alcohol consumption among husbands. The study finds no change in women's attitudes after short-term increases in IPV but observes rising tolerance following prolonged exposure. Women may adjust their acceptance of IPV in response to persistent violence, especially when they have limited opportunities to leave abusive relationships.

This highlights an important nuance: Changes in IPV-tolerance attitudes may not only reflect a shift in bargaining power from changes in outside options, but may also be an adaptive response to constrained choices. When women are exposed to recurrent violence and economic insecurity, they may psychologically rationalize IPV as acceptable in order to manage distress and maintain family cohesion. Thus, when women's financial independence and exit options are limited, in addition to losing agency status within the home, they may also rationalize IPV as an unavoidable part of their reality. These mechanisms may also operate concurrently as IPV tolerance may reflect changing fallback options as well as adaptive responses to economic vulnerability, further underlining the strong association between acceptance of IPV and the experience of it.

Prolonged droughts or other climate-induced stressors may lead to increased experience of violence within the home for the multiple channels discussed above, increasing women's tolerance of IPV. This again implies that acceptance of IPV is a good proxy for actual experience of it, especially in the relatively longer run. This is also important as it frames IPV tolerance as both a reflection of

women's vulnerability to economic and environmental stressors, and, depending on the circumstances, a potential response to it. These factors will be discussed further below.

In summary, the studies discussed above indicate that using IPV tolerance as a proxy for IPV experience is a valid approach. Climate shocks that affect employment, household income, relative bargaining power, and gender roles may influence both the likelihood of IPV experience for women and their acceptance of it. Thus, IPV tolerance, while possibly reflecting both adaptive coping and changing economic circumstances, provides a reliable indicator of IPV risk, especially in settings where direct experiences of violence are likely to be underreported. Given the limitations of consistent IPV experience data in the Bangladesh DHS, using women's attitudes toward IPV provides a validated proxy measure that allows us to assess how climate change influences violence dynamics within the home.

3. Background and data

Bangladesh has 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.[6] 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.[7]

[6] See the Global Climate Risk Index (CRI) of 2021 by Germanwatch, available at https://www.germanwatch.org/en/cri.

[7] 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) find 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%.

3.1. Gender roles, women's agency, and experience of intimate partner 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.[8] 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. Figure 1 shows the location of BDHS clusters in 2007 (on the left), and for the three other years (on the right).[9] We separate in this manner since 2007 is the only year in which we have a measure of the actual experience of IPV, as noted above. On average, each district contains 10 clusters, with an average of two clusters per sub-district.

3.1.1. Women's attitude towards intimate partner 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 attitudes, women's agency, and experience of IPV.[10]

We begin by using variables related to attitudes towards physical violence. These attitudes provide insight into women's perception of their own status (NIPORT 2013), while also reflecting other dimensions of women's status (such as 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

[8] 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*.

[9] To protect privacy, the DHS geocodes are randomly offset by up to 5 kilometers in location. However, the displacement procedure ensures that the clusters remain within the same administrative units so that the data can be analyzed appropriately within administrative frameworks. For more details, please see Burgert et al. (2013). Michler et al. (2022) show that such locational offsets have limited to no impacts on estimates.

[10] The 2007 BDHS round also assessed women's attitudes towards intimate partner 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 intimate partner violence, we use these data separately to construct variables pertaining to exposure to intimate partner violence. These results are reported separately.

the children; and (v) refuses intimacy. Following the literature, we create an index dummy variable that equals one if the woman agrees with at least one of these five statements.

Our study focuses on women's attitudes toward IPV, following established research methodologies (Bisika 2008; Mitra et al. 2021; Mwale 2023; Mwale et al. 2021; Thompson et al. 2007). As discussed above, IPV attitudes are a reliable proxy for IPV experience, and using attitudes addresses challenges in collecting accurate self-reported IPV data in traditional patriarchal settings like Bangladesh where deeply ingrained norms may influence reporting. 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. Thus, information on attitudes provides a more reliable measure of IPV prevalence in contexts with cultural stigma. This method of collecting information may also help mitigate issues associated with recall bias, enabling a more accurate measure of dynamics.

3.1.2. Experience of intimate partner violence

While the majority of our analyses use information on tolerance of IPV, we also use the intimate partner 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. The survey measured intimate partner 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 intimate partner violence (see Cools et al. 2020; Kishor 2005; La Mattina 2013). 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.[11] We code dependent variables for the experience of physical and/or sexual violence, similar to the measure for acceptance of IPV described above.[12]

3.2. Weather variables

Weather data is obtained from the ECMWF Reanalysis v5 (ERA5) product provided by the Copernicus Climate Change Service, a reanalysis product that focuses on agrometeorological indicators including temperature, precipitation, air pressure, wind speed, and solar radiation, available at a spatial resolution of 0.1° x 0.1° (Boogaard et al. 2020).[13] We construct monthly averages for these variables from the daily time series, and then link each DHS cluster to the weather data on the basis of geo-codes.[14]

We use inverse-distance matching to obtain local (cluster) measures of climate by calculating the weighted average of the 5 closest grid points, weighing each point by the inverse of the distance from the cluster's centroid.[15] This approach is commonly used (Mendelsohn et al. 1994; Deschenes and Greenstone 2011; Zhang et al. 2017). We check for robustness with 1, 3, and 10 closest grid points.

[11] In adherence to WHO's ethical and safety guidelines for intimate partner 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 intimate partner 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 intimate partner violence data confidentially and ethically.

[12] 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 be intimate even when you did not want to?"

[13] 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 are available on request.

[14] The distributions of the additional weather variables are also likely to be affected by climate change.

[15] We apply this technique as we are evaluating the weighted average of the closest grid points, not the closest gridded areas. Python codes are available on request.

3.2.1. Evidence of climate change

Figure 2 presents 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 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.[16]

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, and 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).[17]

[16] 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).

[17] "*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.

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 one 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 acquired information related to project names, implementing agencies, estimated costs, start dates, as well as both scheduled and actual end dates for several projects. We extracted location data from the project titles, supplementary documents available on the portal, and resources from the 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 58% 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.[18] Panel D presents the statistics for the set of controls used in our regressions.

4. Empirical strategy

In constructing weather shocks, we follow the literature and consider deviations of rainfall and temperature from their long-run local averages over the period 1980 through 2000. These shocks are 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 average by at least one SD, zero otherwise. Cluster-specific monthly averages 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 one 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 mean by at least one SD. The choice of one SD as a deviation metric is consistent with other studies (Abiona and Foureaux-Koppensteiner 2018; Dell et al. 2014; Ibanez et al. 2021), and we check for robustness of this measure by repeating the analyses with the Standardized Precipitation Evapotranspiration Index (SPEI), an alternative drought and heat metric.[19]

[18] 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.

[19] Estimation results using SPEI are presented in Table A1, Panel E.

We follow Hsiang et al. (2013), Burgess et al. (2014), Iyer and Topalova (2014), and Tsaneva (2020) to define our key climate variables as the number of months during the past 3 years (36 months) in which a climate shock (drought, excessive rain, or extreme heat) occurred.[20] Our specification is:

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

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 at least one 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 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.[21] The omitted temperature bin is (20-25]°C, which is considered to be "comfortable." We include rainfall in the month and year of survey in a quadratic form following Zhang et al. (2017). The vector of climatic variables W_{cdmt} is thus as in equation (2):

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

[20] 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 intimate partner violence. Third, we limit the time interval as adaptive responses may become important in the absence of an upper time bound.

[21] 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).

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 children (below the age of 5) in the household.

Equation (1) also includes district-by month, ω_{dm}, and district-by-year, μ_{dt}, fixed-effects to 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 following Abadie et al. (2023).[22]

The identifying assumption for our parameter of interest, β, is that conditional on the controls for contemporaneous weather, location-specific seasonality, and on other characteristics, 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 intimate partner violence

5.1. The impact of weather shocks on acceptance of intimate partner violence

Table 2 presents results from the main regression in equation (1). Column (1) shows results from the full sample; we find 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 one SD increase in the frequency of dry months raises the probability of IPV acceptance by approximately 2.5 percentage points for women in

[22] Our results are robust to accounting for spatial error correlation as in Conley (1999).

these communities. In communities not dependent on agriculture, we find no effect. We find few effects of wet and hot months in both sub-samples.[23]

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, 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.[24] 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 lack of visible and immediate impacts, which hinder rapid responses and resource mobilization. Bangladesh also has

[23] 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 intimate partner violence for a group of 38 countries. Abiona and Foureaux-Koppensteiner (2018), in their analysis of household shocks on intimate partner violence in Tanzania also find no impact of wet shocks on the incidence of intimate partner 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. (2024) 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.

[24] Vitellozzi and Giannelli (2024) analyze 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) assess 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) highlight 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.

less developed infrastructure to manage water scarcity, which compounds impacts. Our finding that primarily droughts have impacts is not unusual. Díaz and Saldarriaga (2023) also show that adaptive capacities in the Peruvian Andes are not developed enough to manage 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 agricultural settings, we may be losing precision for heat shocks as heat and drought are correlated.[25] We find support for this in the climate science literature where it has been noted that droughts and heatwaves are driven by similar underlying factors in the face of accelerating climate change, thus resulting in 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 in Table 2, 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.[26] 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 one SD increase

[25] Extreme heat conditions are associated with less cloud cover and humidity, which, in turn, suggests less rainfall. We find that in our sample, 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).

[26] We examine results separately 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.

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.[27]

5.2. The impact of weather shocks on experience of intimate partner violence

To complement our analysis on attitudes towards IPV, we use data from DHS 2007 to estimate effects on the experience of IPV for women employed directly in agriculture, presuming that coping responses and deteriorating outside opportunities for women in agriculture who are especially exposed to climate shocks may increase IPV (Farmer and Tiefenthaler 1997).[28] We find supporting evidence in Table 3, which reports a positive association between the frequency of dry months and IPV experience.

5.3. Heterogeneous analyses and effects by decade of birth

5.3.1. Effects by residence, literacy, and prosperity

In Table 4, we perform heterogeneity analyses for the lowest wealth quintile of households.[29] We split the sample along three dimensions: sectoral residence, literacy status, and local economic prosperity (nightlights). These characteristics may shape exposure to climate-sensitive income streams, women's outside options, and the flexibility of local normative environments, respectively. Given our main results showing that effects are concentrated among poorer and agriculture-dependent households, this heterogeneity is informative because it helps identify which structural constraints within vulnerable groups matter most. These dimensions therefore allow us to understand how drought impacts may be amplified or dampened in different contexts, consistent with the idea that climate shocks can influence acceptance of IPV through multiple pathways.

[27] We 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 main analysis. We do not find any effects of dry shocks, which may be attributed to the relatively small sample size.
[28] 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).
[29] Results for the other sub-samples are available upon request.

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. This pattern aligns with settings where income losses from shocks may be more salient and fallback positions more limited, potentially consistent with a bargaining mechanism.

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. Literacy may correlate with better economic prospects, information access, and stronger fallback options. Consistent with this, we find that the main negative effects are concentrated among illiterate women.

Finally, we check whether effects vary across levels of economic prosperity. These results shed light on a potential economic channel: The reduction in women's options may be more pronounced in contexts where shocks more strongly reduce local economic activity. We use satellite data on cluster-specific nighttime light intensity in the survey year as a measure of local development (Henderson et al. 2012), and classify respondents into high or low prosperity areas based on whether light intensity is above or below the 50^{th} percentile of the distribution. Columns (5) and (6) show that there is a detrimental impact of dry months in less prosperous clusters only.

5.3.2. Effects by decade of birth

Cohort heterogeneity is useful to examine in this context because women born in different decades were exposed to different average normative environments, different average levels of education, and different baselines of economic opportunity over their life cycle. If climate shocks affect women's relative position partly through channels related to economic dependency, stress, and norms, then younger and older cohorts may respond differently.

In order to estimate cohort effects, we augment equation (1) with indicators for women's birth decades, and include separate interaction terms for the frequency of dry months and 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 A2.

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.

This finding is striking given that younger women in Bangladesh have, on average, higher schooling, greater exposure to information technologies, and more potential access points to external support networks. The results suggest that when climate shocks intensify and become more frequent (as has been the case in more recent decades), these advantages may not translate into stronger protection within the household. The cohort gradient is consistent with settings in which economic stress is harder to buffer for younger groups, where reallocation of tasks or earning responsibilities for coping are more contested, and where climate-related instability can interact with existing gender hierarchies to reduce women's bargaining power.[30]

5.4. Climate shocks, women's agency, and bargaining power

To assess whether droughts operate through a bargaining channel, we examine how climate shocks affect women's agency within the household. Women's participation in household decisions and control over earnings provide key dimensions of their bargaining power and outside options. If droughts disproportionately weaken women's economic position, they should reduce women's agency

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

along these margins, and these reductions would drive higher tolerance of IPV. We test these predictions by analyzing how drought exposure affects multiple dimensions of women's agency, and by examining whether agency moderates the relationship between drought exposure and IPV tolerance.

In Table 5, we focus on the most vulnerable agricultural households and investigate whether dry shocks impact aspects of women's bargaining power and fallback positions. In Panel A, the analysis is limited to agricultural households (where either the respondent 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 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 decisions on how to use her earnings jointly with her husband.[31]

The results support the hypothesis that a higher occurrence of dry months lowers women's agency. In both panels, dry months increase the likelihood of women's exclusion from decision-making processes and decrease the probability of having control over their cash earnings. These findings

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

indicate that drought exposure disproportionately erodes women's economic and decision-making autonomy in agriculture-dependent and asset-poor settings.[32]

Building on this evidence, we use these same measures of agency to shed further light on the potential channel linking climate shocks to IPV tolerance. Specifically, we examine whether the impact of droughts on women's acceptance of IPV varies with their level of bargaining power. The analysis uses the same four measures of women's agency described above and the same sample structure. The results are presented in Table 6, which provide evidence that agency margins mediate the relationship between drought exposure and IPV tolerance, as predicted by a bargaining framework. In both panels, the interaction between drought exposure and lack of participation in household decisions is positive and statistically significant (column (1)), indicating that droughts have stronger effects on IPV tolerance among women with little influence in household decisions. The interaction between droughts and control over earnings is negative and significant in column (4), showing that women who retain control over their income are less likely to justify IPV when exposed to droughts. These results imply that drought effects are stronger among women with lower bargaining power. These patterns are also more difficult to reconcile with mechanisms driven primarily by male income loss or psychological stress, but are more consistent with variation in women's outside options.

The interactions with the decision-making index and freedom of movement are small and measured imprecisely. However, their signs are mostly as expected. The total effect of droughts, calculated as the sum of the coefficient on the number of dry months and the corresponding interaction term, shows that women with low agency experience net increases in IPV tolerance. The consistency

[32] Another test would rely on direct measures of women's access to independent cash earnings at the local level, but our data do not allow us to construct district-level female cash-earning rates. To address this limitation, we focus on women in the poorest wealth quintile, for whom access to cash income, assets, and outside options is most constrained. In the Bangladeshi context, low household wealth is strongly correlated with limited female labor market participation and restricted control over earnings. The fact that drought effects on agency and IPV tolerance are largest precisely among these women reinforces the interpretation that limited access to cash earnings and economic resources amplifies vulnerability.

of the results across the main agency indicators provides further evidence that deterioration in women's bargaining power is a central pathway through which droughts increase women's acceptance of IPV.

5.5. Alternative mechanisms: Stress and backlash

Climate shocks may also influence IPV through broader labor-market dynamics. The stress channel posits that economic hardship and male job loss heightens financial strain and psychological pressure within households, potentially increasing conflict. The backlash channel suggests that when women increase their labor-market participation, often as a coping response, men may perceive this as a challenge to traditional gender roles and may react violently.

A growing body of evidence provides support. Anderberg et al. (2016) develop a theoretical and empirical framework showing that male and female unemployment have opposite effects on domestic abuse in the United Kingdom. Bhalotra et al. (2021) find in a cross-country study of 31 developing economies that higher male unemployment raises IPV through stress, whereas female employment opportunities can heighten IPV through backlash, particularly in settings where women have limited access to divorce. In Uganda, Clerici and Tripodi (2021) show that male job loss during the COVID-19 lockdown increased women's likelihood of experiencing physical violence by about five percentage points, though the effect dissipated once the shock eased. Similarly, Calabresi (2025) documents that male unemployment in Mexico is associated with a rise in sexual violence, driven by male backlash against women with progressive attitudes. Sanin (2022) provides evidence from Rwanda that women's entry into paid employment, facilitated by coffee mill expansion, reduced violence by improving women's outside options. Yet, as Bhattacharya (2015) notes in the Indian context, women's employment does not automatically translate into empowerment: Women who experience violence work, but lack control over their earnings, suggesting that financial participation without agency can coexist.

Drawing on these insights, we examine whether drought effects vary with local male and female employment conditions. Given the DHS data are not panel in nature, we constructed a proxy for male unemployment based on whether the respondent's husband was reported as not working at the time of the 2011 survey, and then calculated the upazila-level mean of male unemployment in 2011 which was then merged with the 2014 and 2017 samples.[33] For female labor-market participation, we used respondents' employment status, aggregated at the same level in 2011, which was then merged with the 2014 and 2017 rounds. Both indicators are interacted with drought to assess whether IPV tolerance is associated with male unemployment (the stress channel) or female employment (the backlash channel).

The results, which are available on request, reveal no statistically significant effects for the interactions between drought exposure and either male unemployment or female employment. This suggests that the rise in IPV tolerance following droughts is unlikely to operate through household stress or through backlash effects in our context. Rather, the evidence aligns more closely with the bargaining mechanism discussed above, where we find evidence that droughts erode women's outside options.

We provide additional suggestive evidence on stress versus bargaining channels by examining the temporal profile of climate shocks. A stress-based mechanism would typically predict sharp, immediate responses that dissipate as conditions normalize, whereas a bargaining-based mechanism implies cumulative effects as women's fallback positions gradually weaken. Using a distributed lag model (Table A1, Panel D), we find that drought effects mostly persist up to three years after the shock. This persistence aligns with a structural erosion of women's assets and outside options rather than a transient response to acute, short-run stress. However, we cannot definitively rule out stress

[33] Merging the 2011 upazila means for male unemployment and female employment with the subsequent 2014 and 2017 rounds allows us to address the issue that these variables may be changing contemporaneously due to climate shocks.

mechanisms as there is weak evidence that droughts in the past 12 months also increase IPV tolerance.

5.6. Robustness tests for the main results

In Section A1 in the Appendix, we conduct additional robustness tests for the main results with alternative specifications and additional controls. We also analyze monsoon rainfall, growing degree days, and extreme degree days in this section. Results are presented in Tables A1 and A3.

5.7. Wealth and agriculture dependency

In this subsection, we examine whether wealth and agriculture dependency compound each other. In Panels A and B of Table 7, 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 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 in the lowest quintile in agriculture dependent communities. This is in contrast to the 1.0 percentage point effect in column (1). There are no impacts in Panel B that considers communities that are not dependent on agricultural employment.

These findings suggest that in agriculture-dependent communities, economic dependency is likely to be an important factor, particularly among the poorest women. Women in the lowest quintile are often constrained by limited opportunities outside of agriculture, while agriculture is especially susceptible to climate shocks such as droughts. In times of drought, when agricultural productivity declines, these women may feel even more dependent on their male partners given loss of their means of sustenance (individual or otherwise), providing further evidence that bargaining may be key.

To further pin down how agriculture, climate vulnerability and existing socio-economic divides compound effects, 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.[34] 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.[35] The indicator is then constructed based on the quartiles of this index. We next perform regressions including the interaction of our variable of interest and the indicator for high agricultural vulnerability.

With the exception of column (1), coefficients on the interaction terms of dry shocks and the vulnerability index presented in Panel C of Table 7 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.

5.8. Results focusing on agricultural households

We examine whether intra-family employment structure plays a role, with results presented in Table A4. We focus on households where the husband is employed in the agricultural sector. As seen

[34] 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 at the *upazila* level . A list of 12 vulnerability indices constructed using a 30-year average climate data since 1980 is available. The index ranges from zero (no vulnerability) to one (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.

[35] 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. The corresponding data was then normalized, weighted, and aggregated to obtain standardized vulnerability scores for each *upazila*.

in Panels A and B, there are impacts 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 A4 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). There is a protective role played by the additional income contributed by working women, as in Panel C.

6. Climate resilience investments shield women from violence

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.[36] 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

[36] 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).

mitigation, adaptation, and resilience, for example through the adoption of climate-tolerant technologies, biodiversity and environmental initiatives, and by 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 gender disparities, societal norms, and unequal control over resources.[37]

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 on 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. They aim to offset climate-related revenue losses by implementing gender-responsive adaptation strategies.

6.2. Project allocation

[37] 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. 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.[38] 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 details 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"). However, 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 such projects, focusing instead on agricultural projects with complete information. This selection criteria narrows our dataset to 200 projects.[39] 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. As we are able to obtain location data for a subset of all BCCT projects, our "control" group may also have received assistance at some point, leading to a conservative bias in our estimates (Rustad et al. 2020).

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

[39] 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.

Table A5 provides the summary statistics for socioeconomic, geographic, and climate-related vulnerability indices for *upazilas* with and without BCCT projects. 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 constructs 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.[40] While anecdotal evidence suggests that BCCT project allocation does not have an explicit focus on social equity or norms (Rahman et al. 2016, Mujaffor 2019), we conduct a series of robustness checks in Section 6.5. to ensure that results are not driven by placement bias.[41]

6.3. Methodology

Our objective is to quantify the extent to which these climate resilience projects shield women. To this end, we use equation (3) where the variable of interest is the interaction of the frequency of dry months and local climate-aid projects:

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

where $BCCTproject_{sd}$ equals one when the respondent's cluster falls within sub-district *s* in district *d* that had at least one BCCT project at the time the DHS survey was conducted. All other notations 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.[42] We hypothesize that

[40] Empirically, short-term droughts are not correlated with BCCT project allocation after conditioning on fixed-effects.
[41] 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.
[42] The methodology here is similar to Chatterjee and Merfeld (2021).

BCCT projects exert an attenuating influence on the effect of dry shocks, and thus π is negative. The net effect of drought on acceptance of IPV in sub-districts with active BCCT projects is $(\beta + \pi)$. If the *p*-value for this net effect is higher than conventional levels, then we cannot reject that the net effect is statistically zero. That is, BCCT projects serve to buffer the negative effects of dry shocks.

To address possible non-random BCCT project placement, our strategy leverages the staggered timing of project implementation following Knutsen et al. (2017), Kotsadam et al. (2018), and Zhang and Huang (2023). We augment equation (3) with an indicator variable for "inactive" projects: Those planned but not yet implemented at the time of the survey. This allows us to compare the effect of active projects to a placebo group of sub-districts that were also selected for treatment, thereby accounting for unobservable characteristics that may drive project placement. If the attenuation is due to confounding factors, the effects should manifest in locations with both active and inactive projects. We also assess treatment intensity by considering the number of active and planned/inactive projects.[43]

6.4. Results

We present results focusing on agriculture-dependent communities in Table 8.[44] Coefficients on the interaction terms between drought and BCCT projects, π, are negative and measured precisely in columns (1) and (2), indicating that the net effect of dry shocks diminishes considerably with BCCT project proximity.[45] Inactive projects have no effects.

[43] The count of active projects in proximity varies from zero to 11.
[44] Results on the full sample are presented in Table A6. 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 insignificant except in the case of agriculture-dependent communities.
[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.

We next explore how effects vary by 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 BCCT project. Again, inactive projects have no effects.[46]

Table 9 examines attenuation effects from the presence of climate projects based on wealth quintiles. These results corroborate our previous ones to 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. Further, across Tables 8 and 9, joint significance tests for $(\beta + \pi = 0)$ fail to reject the null. That is, BCCT projects mitigate the harmful consequences of dry shocks.[47]

We perform a number of 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. Table A7 presents the results: In column (1), we evaluate women whose primary occupation is in the agricultural sector; in column (2), we include women from households where either the respondent herself or her husband is engaged in agriculture; and in column (3), we focus on women in the lowest quintile who work in any sector, and whose spouses are in agriculture. In all instances, BCCT projects have moderating effects.

6.5. Addressing BCCT project allocation

[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.

[47] Although we anticipated partial attenuation of the main adverse impacts, it is plausible to see stronger 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.

As reported in Table A5, sub-districts receiving projects differ from non-recipient districts along several pre-existing dimensions, and project allocation may be endogenous to underlying local characteristics. We present a number of checks to address non-random placement.

Our first set of checks leverages the staggered timing of BCCT project implementation, presented in Table 8, columns (2) and (4). As noted above, the effects of inactive BCCT projects are insignificant. Further, we explicitly include only those projects that were active at the time of the survey, using their actual start and end dates (Panel B of Table A8), and exclude projects introduced during the survey year (Panel C of Table A8). Our results remain unaltered.

Complementing this placebo-style analysis, we next control for a rich set of pre-BCCT, sub-district level covariates. As presented in Panel A of Table A8, we include a wide array of factors that may influence project allocation including: (i) geographical and economic characteristics such as ground slope, elevation, nighttime luminosity, and sectoral employment shares; and (ii) measures of climate vulnerability proxied by a composite index for crop yield susceptibility and the number of people affected by natural disasters.[48] Across the three columns in Panel A of Table A8, the sign and significance of the interaction terms between dry shocks and BCCT project remain unchanged.

Next, we implement a propensity-score matching estimator by matching treatment clusters that have received BCCT projects during our study period with control clusters *from the same district* that did not receive such projects. Matching leverages cluster-level agricultural and climatic vulnerability,

[48] More specifically, these factors include geographical measures 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 ages of 15 to 64 years; and measures of climate vulnerability including 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 (PM2.5).

geographic proximity, and economic development, with results presented in Table A9.[49] The post-matching estimates are in the same direction and close in magnitude to those in Table 8, but they are noisier, likely because of the reduced sample size.[50]

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 levels of attenuation afforded by BCCT projects.[51] 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.[52] The dataset traces a total of 299 aid initiatives across 3,641 locations in Bangladesh from 2000 to 2015. Figure A2 depicts these projects.

The dataset includes the 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.[53] Following Kotsadam et al. (2018), we limit our analysis to projects with precise geocodes and with information on when

[49] More specifically, treatment and control clusters are matched based on district (exact match) plus agri-food vulnerability (agricultural, fish/aquaculture, and infrastructure vulnerability indices), climate vulnerability (heat, water, groundwater, and natural disaster vulnerability indices), geographical proximity (latitude, longitude, distance to coast, and rural status), and economic development status (logarithm of nighttime light density). Optimal matching is performed based on Hansen and Klopfer (2006) as implemented in Ho et al. (2011).

[50] 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 similar balance tests.

[51] 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.

[52] 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.*

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

they were established and completed. With these restrictions, we have projects in 1,861 locations. We 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 A10. The coefficients for the new interaction terms are negative in Panel A, but significant only in columns (1) and (4) for women in the three lowest wealth quintiles. The interaction terms for BCCT projects remain significant in columns (4) through (6). Panel B shows that the attenuation impact of BCCT projects remains when we condition on the number of other development projects that are within 10 km. These results suggest 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

To conclude this subsection, we note the establishment of the Bangladesh Climate Change Resilience Fund (BCCRF) by the government in 2010.[54] The project ended in 2016 due to differences between donors, the World Bank, and the Bangladeshi government.[55] Relying on official BCCRF annual reports prepared by the World Bank, we obtain information from 2012 through 2016. Table A11 provides details on each of the five investment projects under the BCCRF during this time period. Although 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

[54] The BCCRF was owned and managed by the Ministry of Environment and Forests; the World Bank provided oversight.
[55] 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.

2012 to 2016, zero otherwise. We then re-estimate our model while excluding respondents in areas that benefited from multiple types of projects; estimates in Table A12 show that our results remain.[56]

In summary, the checks we implement in order to ascertain the robustness of results for 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, netting out projects that were active in the past but are not currently so, netting out projects that became active in the year of the survey, implementing methodologies such as propensity-score matching, and conditioning on the presence of other development projects in the sub-district.

6.7. 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 and directly associated with the stress, bargaining and backlash channels discussed above. BCCT could facilitate agricultural adaptation and resilience when facing droughts thus reducing household stress by buffering agricultural production (for instance, through irrigation and infrastructure investments), provide direct income support in the case of disasters or during times of food insecurity, again reducing stress by strengthening household resilience, and improve women's agency and access to information through institutional and capacity-building programs tied to improving their mobility and earnings, which improves their bargaining capacity. We present evidence on these factors below.

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, and local economic conditions.

[56] 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.

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.[57] 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 one km. NDVI has been widely used to predict and forecast *aman* (monsoon) season rainfed rice in Bangladesh (Faisal et al. 2019; Islam et al. 2021; Mamun et al. 2021; Shew and Ghosh, 2019). 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 measure growth in yields and to difference out components of NDVI that experience minimal changes within each (growing) season. We then estimate regressions similar to that of equation (3), replacing the outcome variable with 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 10.

We find that drought affects multiple margins of rainfed agricultural production (He and Chen 2022; Ji and Cobourn 2021), and such loss could exacerbate intimate partner violence (Bollman et al. 2025). 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). For irrigated agriculture, we find that dry shocks decrease land allocated to irrigated crops (column 3); there are few mitigation effects in column (4). Conclusions from multiple hypothesis testing corrections (Anderson 2008) mostly do not change these estimates (full set of results available on request).

[57] 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 seek to evaluate how BCCT projects influence other measures that may be explanatory and explicitly tied to the stress and bargaining channels discussed above. Table 11 presents results on the impacts of BCCT projects on outcomes that are related to women's agency including 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, in utilizing transport facilities such as bicycles, motorcycles or cars, and in improving access to electricity. These effects are more pronounced among the poorer quintiles. Again, conclusions from multiple hypothesis testing corrections (Anderson 2008) mostly do not change these estimates (full set of results available on request).

In order to emphasize the policy relevance of these findings and in order to clearly highlight which options are most effective in terms of adaptation policies, we end this section by linking these BCCT results to the channels discussed above. Access to media as well as improvements in earnings and mobility are likely to strengthen women's bargaining power by improving their outside options. Increasing awareness of circumstances beyond their immediate environment likely raises knowledge about what is acceptable and what is not. Similarly, increases in mobility may enable women to access alternative markets which may also contribute to improving their cash earnings and thus their fallback positions. Access to electricity may facilitate non-agricultural income streams (such as from women's self-employment) that are likely more protected against climate shocks, insulating overall household income and thereby increasing agency. While we are not able to explicitly estimate infrastructural and technological investments funded by the BCCT given lack of data, infrastructural improvements like rehabilitating irrigation canals and river embankments, or promotion of more hardy seed varieties, will likely enhance disaster preparedness, further contributing to household resilience.

Our evaluation of the stress, backlash and bargaining channels above indicates that in our context, bargaining appears to be the main medium by which climate shocks such as droughts affect women's acceptance of IPV. The fact that BCCT projects enable access to factors that contribute to improving women's fallback options including improving access to media, earnings, mobility, and productive inputs such as electricity as evident in Table 11, provides clear pathways through which BCCT projects serve to attenuate the negative impacts of droughts. These measures function as outside-option "insurance."

These results may also inform how changes in women's acceptance of IPV in BCCT-treated areas should be interpreted. As discussed in Section 2.2, IPV tolerance may reflect multiple, non-mutually exclusive processes including shifts in beliefs about the acceptability of violence as well as adaptive coping responses formed under conditions of prolonged exposure to violence, economic insecurity, and constrained exit options (Frezza 2025). Unfortunately, disentangling their relative importance (and measuring changes in beliefs) would require richer longitudinal individual-level data on IPV experience, norms, and economic constraints, which we do not have at our disposal. Thus, our analysis adopts a norm-centered interpretation that allows for adaptive coping mechanisms to operate alongside belief-based processes, without requiring us to treat them as mutually exclusive.

However, the evidence presented above suggests that increases in IPV tolerance arise as a response to heightened vulnerability, rather than reflecting a purely psychological adjustment to lived circumstances. That heightened vulnerability in response to climate shocks is key is underlined by our results that show that strengthening women's agency measures (as BCCT projects allow) mostly subsumes the negative impacts of droughts. If IPV tolerance was mostly an adaptive belief formed under constraints, then, assuming that beliefs take some time to change, such reversals in response to changes in specific agency measures should be more muted (and take longer time to become evident).

The protective role afforded by the domestic climate resilience funds suggests that IPV acceptance documented earlier in our study more likely reflects a coping mechanism consistent with constrained agency, rather than persistent belief changes. Thus, the mitigating effects of BCCT projects on IPV tolerance work by expanding women's fallback options, thereby reducing the perceived inevitability of violence. The patterns of heterogeneity we document including within-agriculture differences by women's employment status and agency, the cumulative nature of drought exposure, and the agency-linked mitigating effects of BCCT projects, are more naturally interpreted through a bargaining lens.

6.8. Discussion

The evidence we provide 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; 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 intimate partner 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 other externalities generated by climate projects such as adaptive investments to reduce risks. Further, our finding that BCCT projects are more effective than other types of development assistance suggests a need for more targeted interventions in these 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 meteorological and other data with a comprehensive set of indicators on women's agency in the Bangladesh Demographic and Health Surveys, we demonstrate the significant impact of climate shocks on intra-household 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.

A key contribution of this paper is to show that these effects operate primarily through constraints to women's bargaining power. Dry shocks weaken women's agency by reducing participation in household decision-making and control over earnings, and drought effects on IPV tolerance are significantly larger among women with weaker bargaining positions. While stress- or identity-based mechanisms cannot be ruled out entirely, the heterogeneity patterns we document across wealth, sectoral dependence, women's employment status, and agency, are most naturally interpreted as reflecting deteriorations in women's outside options in climate-sensitive settings.

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. 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 mobility and increase their access to information and cash earnings, thus improving their fallback options.

Our results have important policy implications. They highlight 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 such interventions are found to have measurable positive spillover effects that safeguard women's well-being. Providing women with greater access to financial resources and improving their awareness and mobility such that they may participate in economic realms more meaningfully, enhances their resilience to climate shocks.

Our findings also have implications for the design of climate and social protection policies. The evidence that droughts increase women's acceptance of IPV indicates that climate shocks can exacerbate women's vulnerability within households, either by reinforcing adaptive coping or by influencing beliefs about the acceptability of violence. This highlights the need for policy measures that are responsive and flexible to ground realities. If higher IPV tolerance reflects coping or resignation in the face of increased insecurity, then climate resilience investments such as BCCT projects that stabilize incomes expand women's fallback options, thus mitigating violence-related outcomes by lowering the perceived inevitability of abuse.

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 environmental

stressors. By evaluating the ameliorative effects of domestically-funded initiatives, our research offers hopeful insights into the design of policies that may protect at-risk groups in the face of continuing climate crises.

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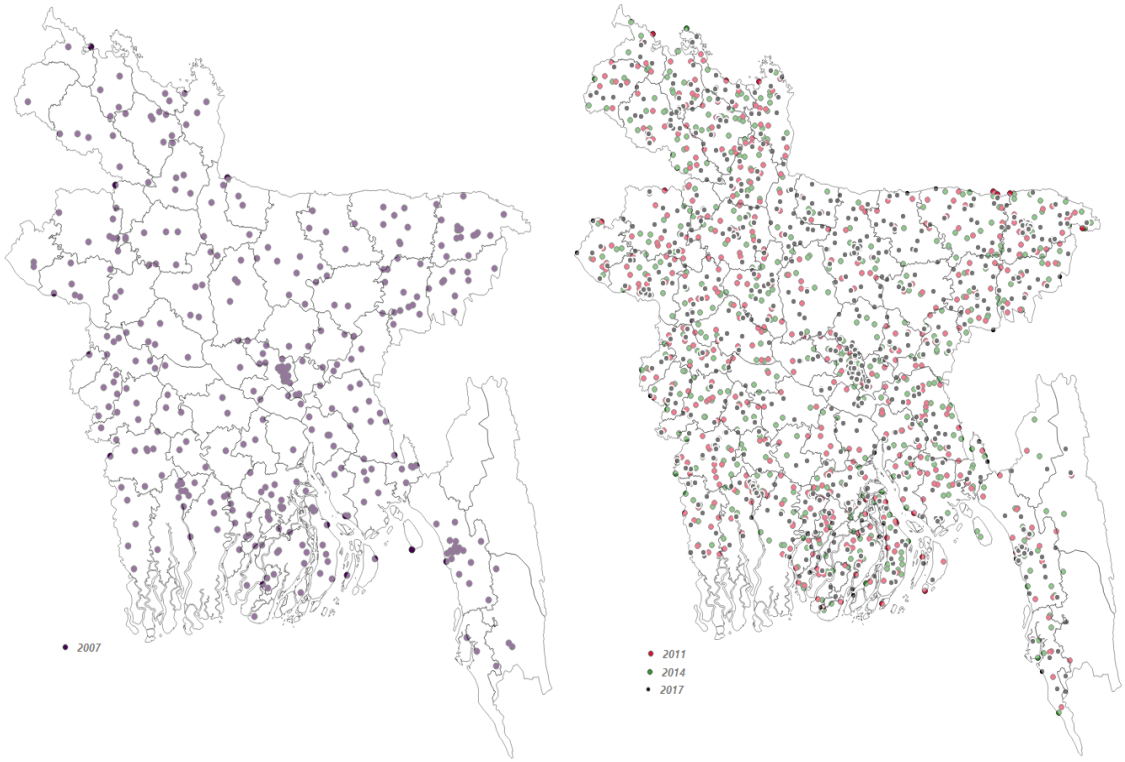
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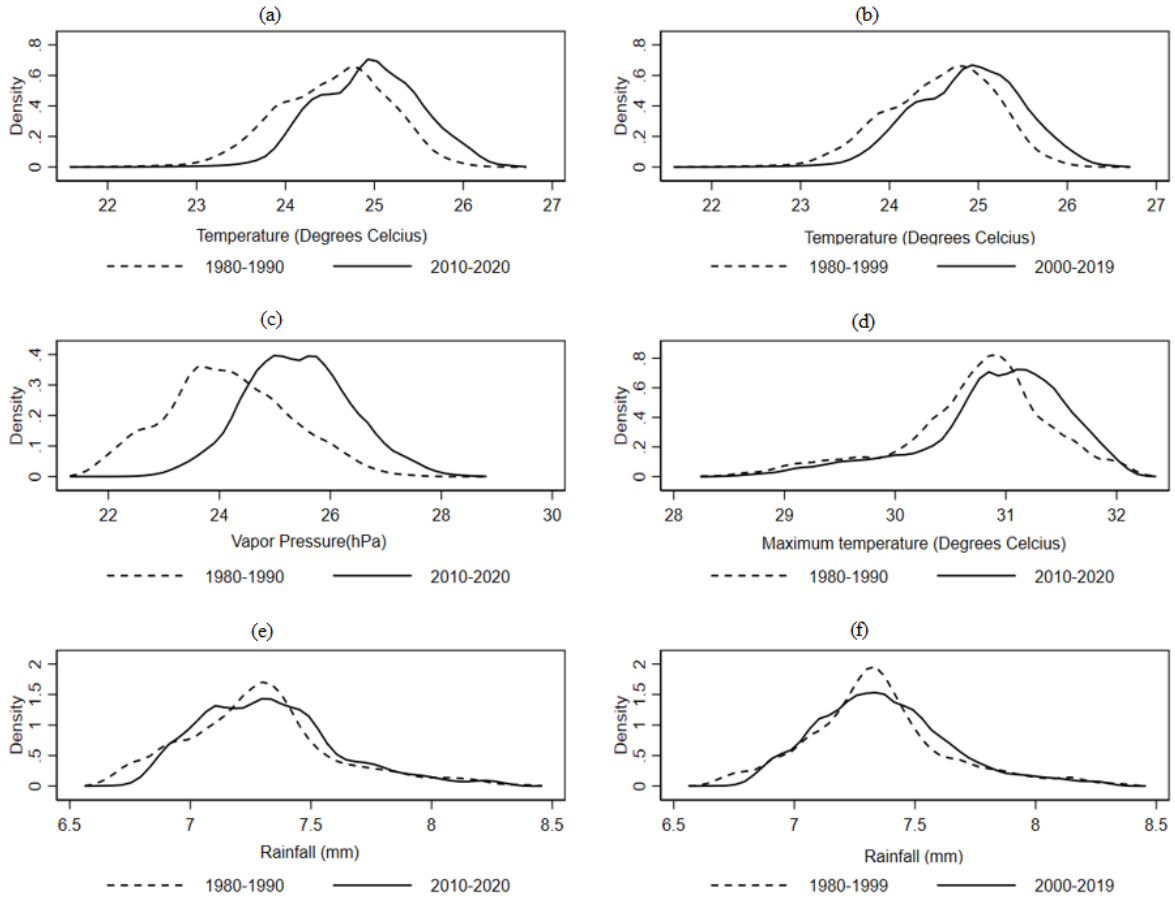
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Figure 1: Location of BDHS clusters



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 sub-district 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 intimate partner 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 one SD of historical average rainfall)		
Number of wet months	4.420	1.734
(above one SD of historical average rainfall)		
Number of hot months	17.423	3.252
(above one 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 one 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 one 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 one 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 fixed-effects	✓	✓	✓	✓	✓	✓
District x Year of survey fixed-effects	✓	✓	✓	✓	✓	✓

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 quintiles. 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 effect of climate shocks on the experience of IPV

	Sample restricted to: women employed in agriculture			
	Form of intimate partner 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 one 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 one 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 one 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 intimate partner 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 4: 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 one 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 one 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 one 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 fixed-effects	✓	✓	✓	✓	✓	✓
District x Year of survey fixed-effects	✓	✓	✓	✓	✓	✓

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 5: The effects of climate shocks on women's 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 one 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 one 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 one 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 one 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 one 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 one 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 fixed-effects	✓	✓	✓	✓
Month, year of survey fixed-effects	✓	✓	✓	✓

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 "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 6: Drought and IPV tolerance: interaction with women's agency

	Dependent Variable: Justifies IPV for at least one reason			
	(1)	(2)	(3)	(4)
Panel A: Agricultural households in the lowest wealth quintile				
Number of dry months (past 3 years)	0.021	0.034***	0.033**	0.047***
	(0.013)	(0.009)	(0.016)	(0.011)
Number of dry months x no participation in decision-making	0.048***			
	(0.017)			
Number of dry months x decision-making index		-0.013		
		(0.008)		
Number of dry months x freedom of movement			-0.004	
			(0.014)	
Number of dry months x control over earnings				-0.025***
				(0.008)
Total effect for number of dry months	0.069	0.021	0.029	0.022
p-value	[0.001]	[0.013]	[0.046]	[0.014]
Observations	991	2,848	992	2,358
R-squared	0.230	0.133	0.221	0.147
Panel B: Women in the lowest wealth quintile, employed in agriculture				
Number of dry months (past 3 years)	0.009	0.038***	0.019	0.049***
	(0.016)	(0.011)	(0.020)	(0.012)
Number of dry months x no participation in decision-making	0.073***			
	(0.018)			
Number of dry months x decision-making index		-0.014		
		(0.009)		
Number of dry months x freedom of movement			0.005	
			(0.016)	
Number of dry months x control over earnings				-0.022***
				(0.008)
Total effect for number of dry months	0.082	0.025	0.024	0.028
p-value	[0.001]	[0.006]	[0.189]	[0.007]
Observations	730	2,502	731	2,049
R-squared	0.271	0.136	0.253	0.155

Notes: The table presents results for the number of dry months and their interactions with measures of agency. Definitions of "no participation in decision-making," "decision-making index," "freedom of movement" indicator and "control over earnings" are as defined in the text. 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. In both cases, we consider the lowest wealth quintile. All regressions include the same controls used in the main analysis, and district, month and year of survey fixed effects. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table 7: 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 one 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 one 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 one 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 8: Climate shocks, attitudes towards IPV, and BCCT projects

Dependent Variable: Justifies IPV for at least one reason				
	Sample restricted to: Respondents in agriculture-dependent communities			
	(1)	(2)	(3)	(4)
Number of dry months (past 3 years)	0.011**	0.010**	0.011**	0.010*
(below one 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 9: 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 one SD of historical average rainfall)	(0.005)	(0.005)	(0.006)	(0.008)	(0.005)	(0.005)	(0.006)	(0.008)
BCCT project (active before survey)	0.062*	0.077*	0.038	0.080	0.061*	0.075*	0.037	0.076
	(0.036)	(0.040)	(0.046)	(0.074)	(0.036)	(0.040)	(0.046)	(0.074)
Number of dry months x BCCT project	-0.018**	-0.020**	-0.020**	-0.035**	-0.018**	-0.020**	-0.020**	-0.035**
	(0.008)	(0.008)	(0.010)	(0.014)	(0.008)	(0.008)	(0.010)	(0.014)
Inactive BCCT project (active after survey)					-0.011	-0.034	-0.034	-0.094*
					(0.037)	(0.041)	(0.048)	(0.055)
No. of dry months x inactive BCCT project					0.002	0.005	0.005	0.012
					(0.005)	(0.006)	(0.007)	(0.009)
Joint test: 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 10: The mitigating effects of BCCT projects

	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)	-0.004*	-0.004**	-0.010***	-0.010***	-0.004*	-0.005**
(below one SD of historical average rainfall)	(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)		0.005*		-0.002		0.010**
x Active BCCT project		(0.003)		(0.004)		(0.004)
Degree Days	✓	✓	✓	✓	✓	✓
Heat and wet months	✓	✓	✓	✓	✓	✓
District x Year fixed-effects	✓	✓	✓	✓	✓	✓
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. Conclusions from multiple hypothesis testing corrections (Anderson 2008) mostly do not change these results. Results available on request.

Table 11: 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. Conclusions from multiple hypothesis testing corrections (Anderson 2008) mostly do not change these results. Results available on request.

Appendix

Section A1. Robustness tests for the main results

Alternative specifications and additional controls

We consider additional checks in Table A1 to ensure robustness. 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 their current residence.[58] Our estimates remain for agricultural-dependent communities and for respondents in the three poorest quintiles, with larger magnitudes as compared to Table 2.[59] In Panel C, we replace our variable of interest with exposure to quartiles of dry shocks.[60] 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 pattern is consistent with a bargaining framework where climate shocks lead to a cumulative erosion of assets and women's fallback positions rather than a purely stress-based mechanism where effects would be expected to dissipate once weather conditions normalize, although

[58] 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.
[59] 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).
[60] 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.

we cannot rule out the existence of a stress-based mechanism as well. This result is qualitatively similar to Ji and Cobourn (2021), which also finds cyclical impacts from weather shocks (on agricultural land use).

Panel E uses the Standardized Precipitation Evapotranspiration Index (SPEI) as an alternative measure of drought and wet conditions.[61] We find similar results: Drier/hotter conditions (SPEI<0) increase women's tolerance to IPV, whereas wetter/cooler conditions (SPEI>0) have no impact.[62]

In Table A3, we control for three additional weather-related variables including solar radiation, wind speed and vapor pressure, averaged over the prior 3 years. Our main results remain unaltered.

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. In results available on request, the main results remain robust.

Next, to capture the nonlinear effects of higher temperatures on agriculture, we construct growing degree days (GDD) and extreme degree days (EDD) following standard meteorological

[61] 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 model because temperature is already taken into consideration when calculating PET.

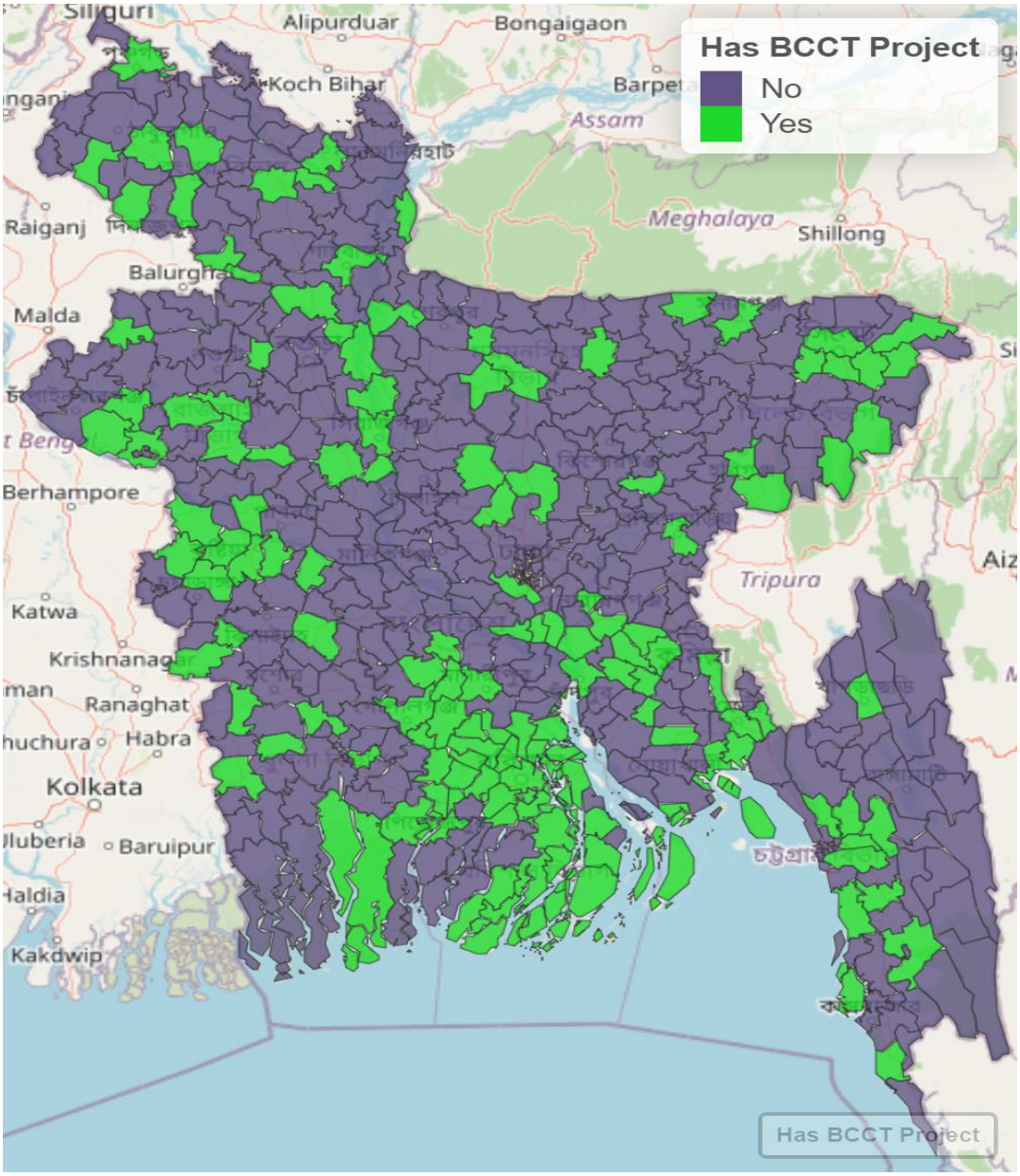
[62] The smaller the SPEI index (the larger in absolute value when SPEI<0), the hotter and drier the weather is. Hence the negative coefficients in Panel E correspond to increases in acceptance of IPV among women in poorer households.

procedures based on Baskerville and Emin (1969) and Snyder (1985), using a threshold of 32^0C.[63] In results available on request, our main estimates again remain robust.

[63] 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.

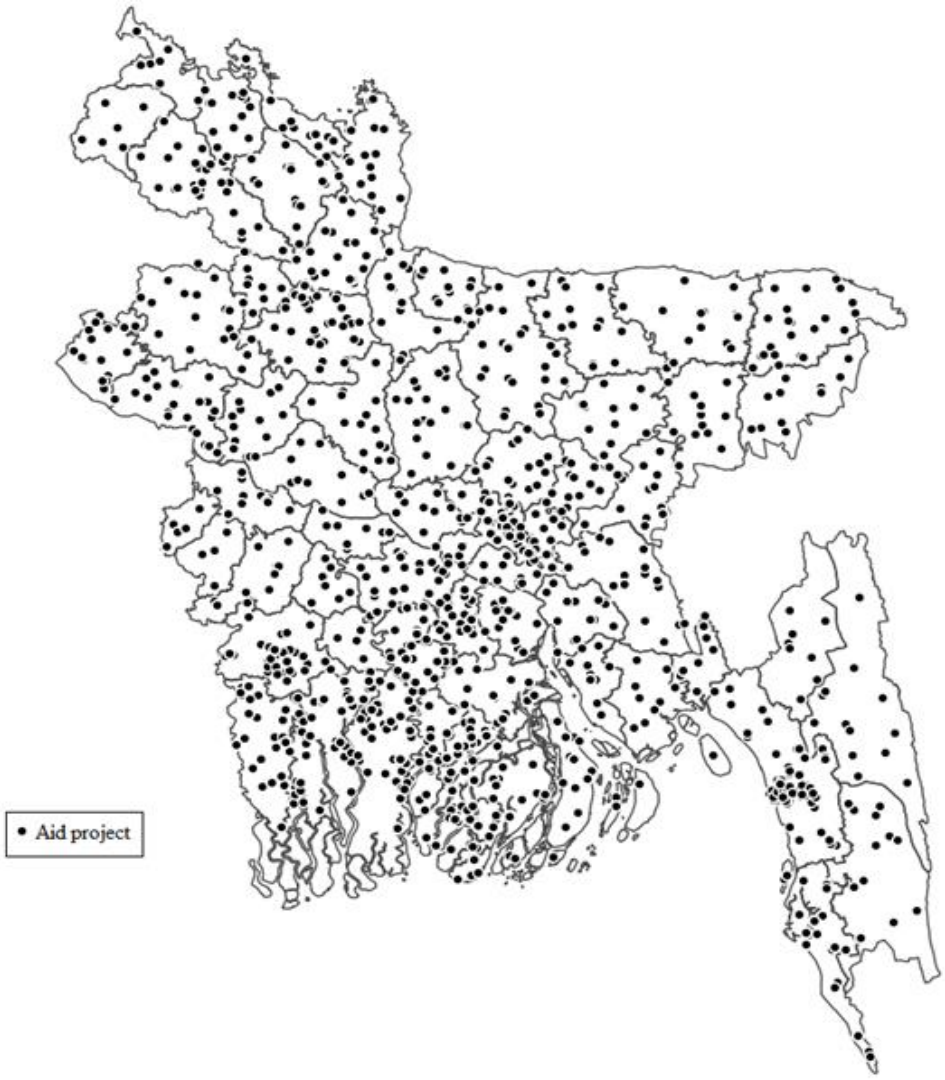
Appendix Tables and Figures

Figure A1: 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: 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 (1)	Agriculture-Dependent Communities (2)	Non-Agriculture-Dependent Communities (3)	Three lowest quintiles (4)	Two lowest quintiles (5)	Lowest quintile (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

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 quintiles. 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, 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 one 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 quintiles. 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 A3: 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 one 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 one 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 one 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 quintiles. All regressions include the same controls and sets of spatial and temporal fixed-effects used in the main analysis, considered in Table 2 and described in the text. All regressions are OLS and are weighted. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A4: The effects of climate shocks on 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 one 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 one 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 one 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 one 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 A5: Summary statistics for sub-districts with and without BCCT projects

	Non-BCCT		BCCT		
	Mean	Std. Dev	Mean	Std. Dev	Difference
	(1)	(2)	(3)	(4)	(5)
Social, economic, and geographic covariates					
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 A6: Climate shocks, attitudes towards IPV, and BCCT projects

	Dependent Variable: Justifies IPV for at least one reason					
	Sample restricted to:					
	All	Agriculture-Dependent Communities	Non-Agriculture-Dependent Communities	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Number of dry months (past 3 years)	0.005	0.011**	-0.009	0.009*	0.011**	0.017**
(below one 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)
Number of dry months x BCCT project	-0.002	-0.018**	0.017	-0.001	-0.002	-0.005
	(0.005)	(0.008)	(0.015)	(0.006)	(0.008)	(0.011)
Observations	47,885	23,108	22,608	27,085	17,703	8,657
R-squared	0.111	0.118	0.120	0.113	0.131	0.157

Notes: The dependent variable is a dummy variable that equals 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 quintiles. 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 A7: Climate shocks, attitudes towards IPV, and BCCT projects

Dependent Variable: Justifies IPV for at least one reason						
	Sample restricted to lowest quintile					
	respondent works in agriculture	resp. or husband in agriculture	husband in agric. and resp. works in any sector	respondent works in agriculture	resp. or husband in agriculture	husband in agric. and resp. works in any sector
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Number of dry months (past 3 years)	0.026*	0.022*	0.040**	0.023	0.020	0.040**
(below one 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 A8: Climate shocks, attitudes towards IPV, and BCCT projects

Dependent Variable: Justifies IPV for at least one reason			
	Sample restricted to: Respondents in agriculture-dependent communities		
	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)
Panel A: With pre-BCCT covariates			
Number of dry months (past 3 years)	0.011**	0.012*	0.024***
(below one 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 one 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 one 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 A9: Estimates of the BCCT moderation effect

	Dependent Variable: Justifies IPV for at least one reason							
	Sample restricted to: Respondents in agriculture-dependent communities							
	Observables used in matching:							
	Agri-food Vulnerability		Agri-food + Climate Vulnerability		Agri-food + Climate Vulnerability + Geographic Proximity		Agri-food + Climate Vulnerability + Geographic Proximity + Economic Proxy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of dry months (past 3 years)	0.011	0.010	0.012	0.013*	0.011	0.012	0.010	0.011
(below one SD of historical average rainfall)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
BCCT project (active before survey)	0.047	0.051	0.049	0.053	0.048	0.052	0.052	0.055
	(0.039)	(0.038)	(0.039)	(0.038)	(0.040)	(0.039)	(0.038)	(0.038)
Number of dry months x BCCT project	-0.016*	-0.017**	-0.015*	-0.016*	-0.015*	-0.016*	-0.015*	-0.016*
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Inactive BCCT project (active after survey)		-0.006		0.017		0.010		0.002
		(0.054)		(0.049)		(0.049)		(0.052)
Number of dry months x inactive BCCT project		0.006		0.001		0.003		0.004
		(0.008)		(0.007)		(0.007)		(0.008)
Observations	13,388	13,388	13,401	13,401	13,409	13,409	13,430	13,430
R-squared	0.136	0.137	0.140	0.140	0.139	0.139	0.137	0.138

Notes: This table presents post-matching estimates of equation (3). Clusters located in sub-district (upazila) received at least one active BCCT project (treated) are matched to all other clusters within the same district (controls). Optimal pair matching (Hansen and Klopfer, 2006, Ho et al. 2011) is performed. Columns (1)-(2) use agri-food vulnerability measures, including agricultural, fish/aquaculture, and infrastructure vulnerability to match treatment vs. control clusters. Columns (3)-(4) use the same agri-food vulnerability indices plus climate vulnerability measures, including heat, water, groundwater, and natural disaster vulnerability indices. Columns (5)-(6) use the same agri-food and climate vulnerability indices plus latitude, longitude, distance to coast, and a dummy variable for rural status. Columns (7)-(8) use the same agri-food and climate vulnerability indices, geographic proximity, plus the logarithm of nighttime light density. Post-matching estimations are performed by combining matching weights with sampling weights. 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 to one if the respondent's cluster falls within a sub-district that had at least one BCCT project implemented before the survey was conducted. Inactive BCCT project is a dummy variable that equals one if there is a known future BCCT project in a sub-district, but that had not yet been established at the time of the survey. 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. Robust standard errors, reported in parentheses, are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

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

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 one 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 one 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 A11: BCCRF's projects

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

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

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

Dependent Variable: Justifies IPV for at least one reason			
	Sample restricted to: Respondents in agriculture-dependent communities		
	Three lowest quintiles	Two lowest quintiles	Lowest quintile
	(1)	(2)	(3)
Number of dry months (past 3 years)	0.010*	0.011*	0.022***
(below one 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.