Weathering Violence in India: Climate Shocks, Spousal Abuse and Potential Mediating Factors

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Abstract

This study investigates the causal relationship between climate shocks and women's experiences of physical intimate partner violence (P-IPV) in rural India. Using geo-coded weather data linked to domestic violence reports from the two recent rounds of the Indian National Family Health Survey (NFHS 2015–16 and 2019–21), I find that droughts, wet shocks, and extreme heat during the most recent kharif growing season significantly increase the likelihood of women experiencing P-IPV. Specifically, exposure to a drought during the growing season increases the prevalence of less-severe P-IPV by 11.6%, while wet shocks increase severe P-IPV by 30.6%. Heat stress, measured as cumulative degree days above 30°C, is also associated with higher rates of both less-severe and severe IPV. Further analysis suggests that increased economic insecurity, husband's alcohol use and marital controlling behaviors, and a decline in women's empowerment are central pathways underlying these effects. Additional heterogeneity analyses reveal that household characteristics — such as land ownership and bank account access play a protective role by offering formal or informal insurance that helps buffer the harmful effects of drought on P-IPV.

Keywords: climate change; intimate partner violence; India

JEL codes: J12, J16, Q56 and O13

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1 Introduction

Intimate partner violence (IPV) constitutes a substantial portion of crimes committed against women worldwide, with far-reaching negative consequences for the health and well-being of victims and their children (Currie, Mueller-Smith and Rossin-Slater, 2022; Bhuller et al., 2024). In developing countries, economic stress induced by climate shocks has been recognized as an important driver of crime and inter-personal conflict (Sekhri and Storeygard, 2014; Abiona and Koppensteiner, 2018; Cooper et al., 2021; Díaz and Saldarriaga, 2023). With a large population dependent on agriculture, recurring extreme weather events heighten the risk of crimes against women and marginalized communities. Therefore, unpacking the nexus between weather and IPV in this context is both timely and necessary. In this study, I investigate whether and how exposure to climate shocks (such as extreme heat, drought, floods) among women in rural India affect the prevalence of physical IPV, uncovering the plausibility of different mechanisms driving this relationship.

The setting of this study is the context of rural India, a choice motivated by its several distinctive features. India has alarmingly high rates of violence committed against women - reported incidence of physical IPV among married women in India increased from 21.33 % in 2005–06 to 22.50 % in 2015-16, subsequently stagnating at 22.42 % in 2019–21 (Dhamija, Roychowdhury and Shreemoyee, 2025). Moreover, in many low-income contexts, the lack of data combining IPV and individual income sources has made it challenging to investigate the role of income in shaping the relationship between climate shocks and IPV. India's vast spatial heterogeneity in climatic conditions, however, offers an ideal setting for exploring how income fluctuations may influence this relationship. Additionally, with limited access to formal credit markets, rural households in India face heightened vulnerability to adverse income shocks. In the second part of this paper, I explore this dimension further by examining how the impact of drought on P-IPV varies across households with different characteristics—such as land ownership and access to bank accounts — that may enhance their ability to smooth consumption in times of financial hardship.

This study uses spatial data on rainfall levels and daily temperature from the Global Precipitation Climatology Center (GPCC) and CPC Global Unified Temperature and women's experiences of P-IPV from repeated annual cross-sections of the Indian Demographic and Health Surveys for the years 2015-16 and 2019-21. My measure of women's experience of P-IPV relies on the Conflict Tactic Scales used in the DHS survey. I define my measure of drought and wetshock as rainfall levels falling below the 30th percentile or above the 80th percentile of local historical distributions (Corno, Hildebrandt and Voena, 2020). I model temperature non-linearly and capture instances of heat stress by looking at the number of degree days that fall above a certain threshold considered detrimental for crop growth (Carleton, 2017). Conditional on region fixed effects, variations in weather in my study is plausibly exogenous. The main effect is identified by comparing, in a given district, the experience of IPV between women who were exposed and not to climate shocks in the last growing season.

The principal findings of this study indicate that exposure to a drought during the most recent kharif[1] season increases the prevalence of less-severe[2] physical IPV by 11.6%, while exposure to a wet shock raises the prevalence of severe physical IPV by 30.6% compared to periods of regular rainfall. Additionally, sustained injuries from physical IPV increase following both drought and wet shocks in the kharif season, although these effects are less robust when using alternative rainfall shock definitions. Temperature ex-

[1] In India, there are two main growing seasons - kharif (June-September) and rabi (October-December)

[2] In the domestic violence module of the DHS surveys, women are asked whether their partners inflicted upon them specific acts of physical violence (P-IPV). Based on the acts involved, this is categorized as either **less-severe** or **severe** forms of P-IPV. More details on the acts involved are given in Section 3.3

tremes also matter: a one standard deviation increase in cumulative degree days above 30°C raises the prevalence of less-severe physical IPV by 14.29 % and severe IPV by 38.19%. Further analysis suggests that increased economic insecurity, men's alcohol use, marital controlling behaviors, and a decline in women's empowerment within the relationship are central pathways underlying these effects.

Leveraging the spatial heterogeneity of India's climate, I further investigate the role of income in driving these effects by separately examining shocks in the kharif and rabi seasons. Some findings align with the income loss hypothesis, such as droughts in the rabi season increasing IPV only in regions that receive relatively high rainfall during the northeast monsoon (October–December), when rabi crops are sown. Similarly, an increase in cumulative degree days below 20°C in the rabi season — which I show leads to a decline in rabi crop yields — is also associated with a rise in instances of less-severe physical IPV.

Additionally, I examine heterogeneity by the extent to which different household characteristics can mitigate the negative effects of drought during the kharif season on household income and consumption. Land ownership and access to formal banking help buffer the negative effects of drought on IPV, underscoring their importance as resilience factors.

This study contributes to at least two different strands of literature. First, this study adds to the vast literature on weather conditions and IPV against women in developing countries. In the context of Sub-Saharan Africa, three studies find mixed results - Cooper et al. (2021) finds null impact of rainfall shocks on IPV, while (Abiona and Koppensteiner, 2018) and (Epstein et al., 2020) find that exposure to dry shocks increases likelihood of experiencing physical IPV. This heightened impact of droughts on violence against women has also been documented in other countries, including Peru(Díaz and Saldarriaga, 2023) and India(Sekhri and Storeygard, 2014; Blakeslee and Fishman, 2018; Sarma, 2022; Dehingia et al., 2024), a finding typically attributed to drought-induced losses in agricultural output, income, and consumption. In Peru, Díaz and Saldarriaga (2023) highlights the interplay between economic insecurity, poverty-related stress, emotional well-being, and women's empowerment in explaining the relationship between droughts and IPV.

Adding to this literature, I include several important extensions in my study. I examine the effect of weather shocks on several mediating factors, similar to Díaz and Saldarriaga (2023), but in a very different country context (rural India) and culture. Unlike Díaz and Saldarriaga (2023) I consider different methods for aligning the timing of weather shocks with the timing of reported IPV incidents, considering the importance of both lagged and contemporaneous growing seasons. In the Indian context, previous studies have often relied on aggregate (district-level) crime data from the National Crime Records Bureau (NCRB) to study the effects of weather shocks on domestic violence (Sekhri and Storeygard, 2014; Blakeslee and Fishman, 2018; Sarma, 2022). In contrast, I use individual-level data on experience of IPV from the Demographic and Health Surveys (DHS) of India, similar to Dehingia et al. (2024), which allows me to capture the potential drivers of IPV risk at a more granular level.

While Dehingia et al. (2024) use NFHS data from 2015–16 and 2019–21 to assess the impact of droughts on IPV in India, my study differs from theirs in several ways. I focus exclusively on women living in rural India, and I broaden the analysis to include not only droughts but also wet shocks, extreme heat, and cold stress. Moreover, by disaggregating weather shocks across India's two primary agricultural seasons — kharif and rabi — and distinguishing between rainfall and temperature anomalies, I provide a more nuanced understanding of the seasonal and climatic pathways through which environmental stress may heighten IPV risk.

This study also contributes to the literature exploring the role of mitigating factors that moderate the IPV response to aggregate shocks. Tur-Prats (2021) examine how the IPV response to unemployment shocks is a function of different family structures (stem vs nuclear) in Spain. The increased impact of unemployment on IPV is mitigated in stem-family territories, where both partners traditionally contribute to household income. Heath, Hidrobo and Roy (2020) examine the impact of cash transfers on IPV in Mali and find a larger reduction in marital disputes following the transfers in polygamous compared to non-polygamous households. Sarma (2022) finds that participation of women in a workfare program[3] in rural India mitigates the adverse impact of droughts on IPV. In the context of Bangladesh, Guimbeau, Ji and Menon (2024) examines how a formal climate resilience initiative can mitigate the adverse effects of drought on IPV. I add to this literature by exploring heterogeneity by the extent to which different household characteristics can mitigate the negative effects of drought on household income and consumption in the context of India.

I organize the paper as follows: Section 2 describes the data sources used and the the construction of weather variables used in this study. Section 3 describes the empirical strategy and identifies some potential threats to identification. Section 4 presents the main results of this study, and some robustness checks. Section 5 provides evidence on the effect of the mediating factors and mechanisms. Section 6 presents results from the heterogeneity analysis and Section 7 concludes.

[3] The Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) guarantees 100 days of employment to rural households in India.

2 Theoretical Foundations

The theoretical literature on intimate partner violence (IPV) broadly distinguishes between two types of violence: expressive and instrumental. Violence is classified as expressive when the perpetrator derives direct utility from inflicting harm (Aizer, 2010; Card and Dahl, 2011). In contrast, violence is considered instrumental when it is used as a means to achieve specific objectives — such as to extract financial resources or influence a partner's behavior (Bloch and Rao, 2002).

Building on this framework, and following Díaz and Saldarriaga (2022), I identify several key pathways through which weather shocks may affect IPV outcomes:

Poverty related stress pathway:
The climate-induced decline in income and a failure to smooth consumption may result in an increase in IPV through an increase in men's substance abuse, violent reactions or through marital disputes. This is consistent with an expressive interpretation of IPV.

Women's empowerment pathway:
Weather shocks may reduce women's income more than men's, leading to a decline in women's financial autonomy, empowerment and threat point of separation. An implication of the household bargaining models Farmer and Tiefenthaler (1997); Lundberg and Pollak (1994) in this context would be an increase in IPV.
In some cases, rainfall shocks might reduce men's income more than women's. If this threatens men's identity and the socially prescribed norms of male dominance, then the sociological theories of "male backlash" suggest that men would attempt to use violence in this scenario to reassert their dominance[4]. This would lead to an increase in IPV, consistent with an expressive interpretation of IPV. Alternatively, men could also refrain

[4] In culturally conservative societies, where divorce is a stigma, some studies find that increased financial independence of women increases the risk of violence Luke and Munshi (2011)

from abuse in this scenario as a way of keeping their partner in the relationship Díaz and Saldarriaga (2022). This might lead to a decline in IPV, consistent with an instrumental interpretation of IPV.

Exposure reduction pathway:

Weather shocks, by changing the labour market conditions of men and women, may affect the time that a woman spends at home with her abusive partner. If the time spent with an abusive partner increases, then in line with criminological theories of IPV, this would lead to an increase in IPV.

Extraction pathway:

Dowry-related aggression in India may lead men to use violence as an instrument to extract more resources from the wife's family as a consumption smoothing mechanism. Evidence of this channel can be found in (Bloch and Rao, 2002) and (Sekhri and Storeygard, 2014). This is consistent with the extractive or instrumental interpretation of IPV.

The discussion above tells us that there are multiple mechanisms that are interdependent and working in opposing directions. For example, the women empowerment pathway cannot be entirely delinked from the poverty related stress pathway that results from a decline in overall income. Using data from DHS (2015-16 and 2019-21) and IHDS (2004-05 and 2011-12), I attempt to show evidence linked to some of these pathways in a later section.

3 Data and Descriptive Statistics

3.1 Data sources

As outlined in the introduction, information on intimate partner violence comes from the two recent rounds of the Demographic and Health Surveys (DHS) of India, conducted in 2015-16 and 2019-21. The DHS for India is called the National Family and Health Survey (NFHS) and is a large nationally representative cross-sectional survey of households in India which provides information on population, health and nutrition. Experience of IPV is recorded in a specific interview module where only one woman of reproductive age (15-49) per household is randomly selected to respond to this module under strict privacy conditions. Respondents are asked whether their current or most recent partners perpetrated any of the listed acts related to physical/emotional or sexual abuse.

I obtained a time-series (1981-2019) of gridded monthly rainfall data from the Global Precipitation Climatology Center (GPCC) at a spatial resolution of $0.5° \times 0.5°$ latitude by longitude ($0.5°$ corresponds to approximately 56km on the equator). For years 2020 and 2021, I obtained data on monthly rainfall levels from CPC Global Unified Temperature at the same spatial resolution. Gridded daily temperature data is also obtained from CPC Global Unified Temperature at a spatial resolution of $0.5° \times 0.5°$ latitude by longitude for the years 1981-2021. For each district in India, I obtain a single monthly precipitation value and daily temperature value by taking a weighted average of all grid points that fall within the boundary of the district, where weights correspond to the fraction of the district's surface covered by the grid(Díaz and Saldarriaga, 2023). I calculate my measure of rainfall and temperature shocks at the district-month level (to be explained in more detail in the subsequent section), and link it to the individual-level DHS dataset using identifier for district and survey year and month.

Finally, to investigate the effect of rainfall and temperature on outcomes such as household consumption, I obtain data from Indian Human Development Survey (IHDS) 2005-06 and 2011-12, a panel survey of households in India. I link my dataset on monthly rainfall and temperature to the IHDS dataset using household's district identifier and information on survey month and year.

3.2 Sample Selection

To ensure that the livelihood of individuals in my study largely depends on agriculture, I consider women living in rural areas of India. Further, I focus on women who are currently married[5] in both rounds and who have lived in their current district of residence for at least one year. The one year residential window rules out temporary migrants. My resulting sample comprises information on 63616 women across both rounds, located across 506 districts and the 23 major states in India. [6]. To account for changes in administrative boundaries of districts, I merged newly formed districts with their parent districts, resulting in the creation of unique district IDs for 506 districts in both rounds.

3.3 Outcome Measures

For my main analysis, I focus on spousal abuse measures related to physical violence and resulting injuries, as information on these acts do not require women to label them as abusive for reporting them. In contrast, reporting sexual or emotional violence requires identifying these acts as abusive, introducing subjectivity. However, I explore effects on sexual and emotional IPV later in the Appendix. Women interviewed for the domestic violence module in the DHS surveys are asked whether their partners inflicted upon them a series of specific acts related to physical/sexual/emotional abuse in the 12 months preceding the date of survey. Following this, I create a dummy variable for experiencing violence by husbands in the past 12 months. The specific acts of physical violence considered are outlined below.

Physical Violence (P-IPV): push you, shake you, or throw something at you; slap

[5] To ensure that marital status is unrelated to the weather changes in my study, I focus on individuals who were married on or before 2014 for the 2015-16 survey and those who were married on or before 2018 for the 2019-21 survey.

[6] I exclude the union territories of Andaman and Nicobar Islands and Lakshadweep, which are located outside the mainland of India and experience very different rainfall conditions. Additionally, I also exclude the north-eastern states as they experience very different sowing and harvesting periods

you; twist your arm or pull your hair; punch you with his fist or with something that could hurt you; kick you, drag you, or beat you up; try to choke you or burn you on purpose; or threaten or attack you with a knife, gun, or any other weapon. Based on the acts involved, this is categorized into **"less severe"** and **"severe"** forms of P-IPV.

Injuries due to P-IPV: cuts, bruises, or aches; severe burns; eye injuries, sprains, dislocations, or burns; deep wounds, broken bones, broken teeth, or any other serious injuries due to P-IPV.

3.4 Weather shock variables

3.4.1 Definition of growing and non-growing seasons

India has two major agricultural growing seasons - Kharif and Rabi. Crops in the kharif season[7] are sown between June-September and harvested around September-November, while crops in the rabi season[8] are usually sown between the months of October-December and harvested in the winter and early spring (Jan-April)(Garg, Jagnani and Taraz, 2020). The kharif season marks the onset of the summer or the southwest monsoon in India and is essential for crops sown in both kharif and rabi seasons. Most of India receives rainfall during the kharif season months of June-September (as seen in Figure 3). For my primary analysis, I define my main growing season as June to September, covering the kharif season months. Following Garg, Jagnani and Taraz (2020), I define March-May as the non-growing season.

The rabi growing season (October - December) coincides with the arrival of the northeast monsoon, which affects only limited areas of the country, namely the southern and eastern coastal regions (Blakeslee and Fishman, 2018). Crops grown in the dry rabi sea-

[7]Major crops like rice, maize, jowar and bajra are sown during this time

[8]Also includes major crops like wheat and barley

son are water intensive and are very sensitive to temperature fluctuations (Birthal et al., 2014). I utilize this spatial heterogeneity in growing seasons and construct my climate shock measures specific to the kharif and rabi growing seasons in some specifications.

3.4.2 Determining exposure to relevant growing season

The DHS survey records instances of intimate partner violence (IPV) based on a 12-month recall period and does not capture the exact dates of occurrence. To construct my main measure of weather exposure, I match each interviewed woman to the weather conditions from the most recently completed growing season prior to her interview. As shown in Figures 1 and 2, this is defined as follows: for women interviewed between January and September, I use the previous year's kharif season, while for those interviewed between October and December, I use the current year's kharif season. For the rabi season weather conditions, I use the previous year's rabi season weather data across all interview months.

While this approach provides a consistent reference point, it may miss potential lagged or contemporaneous effects. Some IPV incidents may stem from shocks in earlier growing seasons if their harvest periods overlap with a woman's recall period for the IPV incident. Similarly, women interviewed during an ongoing growing season may be affected by contemporaneous weather conditions that shape household expectations about future crop yield. To address these complexities, I adopt two alternative matching strategies.

The first alternative, following Díaz and Saldarriaga (2023) and illustrated in Figure 4, accounts for all growing seasons whose harvest periods overlap with a woman's recall window for IPV. For example, a woman interviewed in November (blue dot) has a recall window covering the harvest periods from two consecutive kharif growing seasons. In such cases, I take a simple average of rainfall or degree-day measures across both these seasons. This method implicitly assumes that IPV is most likely to occur in the post-harvest period when agricultural income is realized and that recall bias is minimal.

The second alternative addresses two additional concerns: the possibility that women recall recent IPV events more vividly, and the idea that household tensions may arise during the sowing season due to uncertainty about upcoming yields. To account for this, I include weather data from the current growing season for women interviewed during the season (June to September), alongside relevant past seasons within the 12-month recall window. As depicted in Figure 5, for a woman interviewed in July (green dot), this means taking a simple average of rainfall or degree-day measures from both the current year's sowing season and the previous year's sowing season.

3.4.3 Definition of weather shocks

Rainfall Shocks:

Figure 4 shows the distribution of the Standardized Precipitation Index (SPI) for both the Kharif and Rabi seasons for the interviewed women in my sample, across rounds 2015-16 and 2019-21. The SPI is calculated as the difference in rainfall levels during each season from the district-specific long run (1981-2012) mean rainfall level, and divided by the long run(1981-2012) standard deviation. Both figures show a long right tail, indicating some very wet growing seasons during the time period of my study.

As my main measure of dry and wet shocks, I follow Díaz and Saldarriaga (2023) and Corno, Hildebrandt and Voena (2020) and construct indicator variables for whether or not rainfall levels in the relevant growing season fell below the 30th percentile (for dry shock) or above the 80th percentile (for wet shock) of the district-specific long-run distribution. For woman i living in district j and interviewed at date d (month and year), let R_{ijd} be the total rainfall level observed in the relevant growing seasons. Let R_j^p be the p^{th} percentile in the distribution of rainfall levels observed during the growing season in district j over a 30 year long time period 1981-2012. Then, my corresponding measures for drought and wet shock are given as under:

$$\text{Rainfall Shock}_{ijd} = \left\{ \begin{array}{ll} \text{Drought}_{ijd} & = \mathbb{1}\left\{\text{R}_{ijd} < \text{R}_j^p\right\} \\ \text{Wet Shock}_{ijd} & = \mathbb{1}\left\{\text{R}_{ijd} > \text{R}_j^p\right\} \end{array} \right\}$$

For my main results, I use the 30th percentile as the threshold for drought exposure and the 80th percentile for wet shock exposure, consistent with observed crop yield effects discussed in the next section. For robustness, I use the Standard Precipitation Index (SPI) and create bins based on deviations from the mean Sekhri and Storeygard (2014). The main results remain consistent and are given in the Appendix-II.

Temperature Shocks:

To capture extreme temperature variations, I follow Carleton (2017) and construct measures of cumulative degree days during the growing season, calculated relative to specific temperature thresholds. These measures account for heat stress (degree days above the threshold) and cold stress (degree days below the threshold). Degree-days are calculated as follows, where t^* is a selected cut-off temperature:

$$\text{Degree Days Above } t^* = \begin{cases} 0 & \text{if } t \leq t^* \\ t - t^* & \text{if } t > t^* \end{cases}$$

$$\text{Degree Days Below } t^* = \begin{cases} t^* - t & \text{if } t < t^* \\ 0 & \text{if } t \geq t^* \end{cases}$$

After translating daily mean temperature to degree-day terms, I aggregate these values to construct cumulative degree day measures for each growing season definition. While the agro-economic literature provides well-established thresholds (t^*) for crop yield responses, there is no empirical consensus on the optimal cut-offs when studying IPV outcomes. Based on the distribution of daily temperatures in my sample, I select $t^* = 30°$ C for the kharif season and $t^* = 20°$ C for the cooler rabi season. Additionally, I test the robustness of this specification by applying multiple threshold values and examining cumulative degree days across different temperature bins.

3.4.4 Weather Shocks and Crop Yields

In this section, I examine how rainfall and temperature shocks affect crop yields in India. To do so, I use district-level annual panel data on crop yields — measured as total production per hectare—sourced from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) dataset for the years 1980–2015.

I estimate separate regressions for kharif and rabi season crops. Given that kharif season weather affects subsequent rabi crop yields, I include controls for kharif season rainfall and temperature when estimating the impact of rabi season weather on rabi crop yields. The kharif season includes crops such as rice, maize, sorghum, pigeon pea, and groundnut, while the rabi season covers wheat, barley, chickpea, and rapeseed. The following regression specification is used to assess the effects of weather shocks on yields:

$$\ln Y_{it} = \alpha_i + \alpha_t + \beta_0 \text{Drought}_{it} + \beta_1 \text{Wetshock}_{it} + \beta_3 \, \text{DDabove}_{it} + \beta_4 \, \text{DDbelow}_{it} + \gamma Z_{it} + \varepsilon_{it} \qquad (1)$$

where i indexes districts, t indexes time, and the dependent variable Y_{it} represents crop yield (log of production per hectare). The variables Droughtit and WetShockit are indicator variables equal to 1 if rainfall during the growing season falls below (drought) or above (wet shock) the p^{th} percentile of the district's historical season-specific rainfall distribution. DDAboveit and DDBelowit capture cumulative degree days above or below the selected temperature threshold t^* in district i and year t.

Figures 7 and 8 in Appendix-I present the estimated effects of rainfall and temperature shocks on crop yields for the *kharif* and *rabi* seasons, respectively, across different percentile thresholds for rainfall shocks and varying temperature thresholds for degree days. In Figure 7, Panel A plots the estimated coefficients for drought (β_0) and wet shock (β_1) across all *kharif* crops, while Panel B focuses specifically on rice, a major *kharif* crop. Moving right along the x-axis, the severity of drought and wet shocks decreases. Drought consistently shows a negative impact on *kharif* crop yields across all threshold levels, leveling off beyond the 30th percentile. Specifically, *kharif* droughts defined at the 30th percentile threshold reduce average *kharif* crop yields by approximately 4.67%. The effect of wet shocks on overall crop yields is more ambiguous, though more rainfall clearly benefits rice yields, as seen in Panel B. This aligns with Corno, Hildebrandt and Voena (2020), who find no consistent relationship between higher rainfall and yields in India, except for rice, where increased rainfall significantly improves yields.

Panel C plots the estimated effects of cumulative degree days (β_3 and β_4). As expected, higher temperatures exert a consistent negative impact on *kharif* crop yields, echoing findings from the existing literature. Specifically, a one standard deviation increase in cumulative degree days above 30°C reduces average crop yields by approximately 1.03%.[9]

For *rabi* crops (Figure 8), conditional on rainfall and temperature in kharif season, rainfall shocks during the rabi season show no consistent effects on rabi crop yields. Only

[9] As shown in the figure, one additional degree day above 30°C lowers the log of crop yields by 0.0001329. Thus, a one standard deviation increase (77.5641 degree days) reduces yields by roughly $0.0001329 \times 77.5641 \times 100 = 1.03\%$.

drought and wetshock defined at the 5th and 95th percentile thresholds show a negative impact on yields. This is consistent with findings in Birthal et al. (2014), who similarly document limited sensitivity of *rabi* crop yields to rainfall fluctuations. This is because *rabi* crops are sown during the dry winter months and rely more heavily on irrigation and residual soil moisture from the southwest monsoon (June–September) season. However, I find that *rabi* crop yields are very sensitive to *temperature* fluctuations during the rabi season, with both hotter and colder temperatures negatively impacting yields. Notably, the magnitude of the temperature effects on crop yields for *rabi* crops is larger than that observed for *kharif* crops.

3.5 Summary Statistics

I present some descriptive statistics of all the women in my sample in column (1) of Table 1. The average woman in my sample is 33.96 years old, has a complete primary education level (corresponds to 1.95), is in the middle household wealth quintile (middle corresponds to $3 \approx 2.94$) and got married in 2002. Around 84% belong to the majority Hindu religion, 79% belong to the lower castes (SC/ST/OBC) and 66% have children under 5 in the household. On average, the sex of the household head is male, and their age is 45.81 years. The husband's education, on average is 2.5 (an incomplete secondary corresponds to a value of 3).

Columns 2, 3 and 4 depict the means of these variables for women exposed to regular rainfall, a dry shock (defined as rainfall falling below 30th percentile threshold) and a wet shock (defined as rainfall falling above 80th percentile threshold) respectively, during the most recent kharif growing season. In columns 5 and 6, I report mean differences for the subsamples of women exposed to a dry shock versus regular rainfall, and to a wet shock versus regular rainfall, respectively. I calculate these differences by regressing each individual characteristic on an indicator for exposure to a dry and a wet shock, controlling for month, year, and district fixed effects. The results show that none of the estimated differences are statistically significant, indicating balance in observed characteristics of women exposed to different rainfall shocks.

4 Empirical Strategy

To examine the direct effect of climate shocks on IPV, I use the following linear regression model:

$$\begin{aligned} IPV_{ijt} = \beta_0 + \beta_1 \text{ Drought }_{ijt} + \beta_2 \text{ Wetshock }_{ijt} + \\ \beta_3 \text{DDAbove}_{ijt} + \beta_4 \text{DDBelow}_{ijt} + X_{ijt} + Z_{jt} + \alpha_j + \alpha_m + \alpha_y + \epsilon_{icjt} \end{aligned} \quad (2)$$

where IPV_{ijd} is an binary variable equal to 1 if woman i residing in district j and surveyed at date t(month m and year y) experienced IPV at any time in the last 12 months. Drought $_{icjt}$ and Wetshock $_{icjt}$ denote exposure to a dry shock or a wet shock during the last growing season. DDAbove_{ijt} and DDBelow_{ijt} denote cumulative degree days above and below temperature threshold t^* during the last growing season. X_{ijd} is a vector of individual characteristics which include marriage year dummies, age and dummies for education of the respondent and her husband, religion, caste, presence of children under 5 in the household, sex and age of household head. These are individual specific characteristics that may also affect the experience of IPV. In Z_{jt}, I control for district-level time varying crop yield determinants such as solar radiation flux, vapor pressure, wind speed and cloud cover. This helps control for potential crop yield determinants that may co-vary with rainfall/temperature (Guimbeau, Ji and Menon, 2024).

α_d, α_m and α_y are district, month and year fixed effects respectively. The district fixed effects control for local specific factors that are fixed over time (such as social norms or average weather conditions). The month and year fixed effects control for seasonal and year specific factors that are common to all districts. ϵ_{ijd} is the idiosyncratic error term. Standard errors are clustered at the district-level, to account for potential serial correlation in error terms across women living in the same district. The regression is also weighted using survey (DHS) sampling weights.

The coefficients of interest are β_1, β_2, β_3 and β_4. While β_1 and β_2 measure the effect of exposure to drought and wetshock, β_3 and β_4 measure the effect of increasing cumulative degree days above and below t^* in the last growing season on the probability of experiencing physical IPV during the past 12 months. The interpretation of these estimates as causal effects relies on the assumption that local rainfall and temperature shocks are uncorrelated with any underlying determinant of IPV.

4.1 Threats to Identification

Endogenous migration, sample selection and compositional bias:
A potential concern in identifying the causal effect of exposure to weather shocks in my study is that households may migrate in response to these shocks. I address this concern in a few different ways: Firstly, majority of internal migration within India take place within the same district - which is the aggregate level at which I define my weather shock measures. According to Census data from 2011, 62% of all internal migrants moved within the same district and 26% were inter-district migrants. Secondly, Table 1 shows that individual's observable characteristics do not systematically vary in response to droughts or wetshocks in the kharif season. Thirdly, I filter my sample by considering women who got married before the weather shock took place, ensuring that my weather shock measures are not correlated with marital status and ruling out the possibility that weather shocks affect selection into the sample.

5 Results

5.1 Main Results: Effects of weather shocks on intimate partner violence

The baseline estimates show that exposure to weather shocks during the main growing season significantly increases the probability that a woman experiences physical IPV (P-IPV) in the past 12 months, whereas shocks during the non-growing season have no detectable effect. These results, reported in Table 2, correspond to specification (2), which includes district, interview month, and year fixed effects, along with controls for individual characteristics and time-varying district-level crop yield determinants. These findings highlight the particular vulnerability associated with shocks occurring between June and September, the primary agricultural season in most of India.

Exposure to drought during the last growing season (defined as rainfall levels falling below the 30th percentile of local historical distribution) increases the likelihood of experiencing less-severe physical IPV by 2.88 percentage points, implying a 11.6% increase in prevalence of recent less-severe physical IPV relative to periods of regular rainfall. Exposure to drought also increases the likelihood of sustaining injuries due to physical IPV by 1.81 percentage points, implying a 23.35% increase in prevalence. Exposure to a wetshock increases the likelihood of experiencing severe physical IPV and injuries due to IPV by 1.90 and 2.31 percentage points respectively. Further, the impact of one additional degree day above 30° C during the last growing season increases the likelihood of experiencing both less-severe and severe IPV. More specifically, for 1 SD ($\approx$ 86.07 DDs) increase in degree days above 30° C, less-severe P-IPV increases by 3.56 percentage points and severe P-IPV by 2.83 percentage points.

The magnitudes of my estimates of exposure to drought during the main growing season on IPV ranges from 11.6 to 23.35% increase in prevalence, similar to estimates found in Sub-Saharan African countries. Effect sizes of exposure to drought on physical IPV reported from other countries include a 65% increase in prevalence in the Peruvian Andes (Díaz and Saldarriaga, 2023), a 50% increase in Tanzania (Abiona and Koppensteiner, 2018), and a 0-25% increase in Sub-Saharan Africa (Cools, Flatø and Kotsadam, 2020; Epstein et al., 2020).

Next, I extend the analysis to include weather shocks from the secondary rabi growing season (October–December), alongside the main kharif season. The results, given in Table 3, show that rabi season wet shocks are associated with a decline in the likelihood of experiencing less-severe physical IPV. Going further, I examine the effects of rabi season shocks on subsamples defined by the share of cultivated area under rabi crops.[10] The results, given in Table 4, show that drought has a positive effect on injuries sustained from P-IPV in areas where the share of cultivated area under rabi crops exceeds the national mean.

Interestingly, I find that an increase in cumulative degree days below 20°C in the rabi season is linked to increases in both less-severe physical IPV and IPV-related injuries. Specifically, a one standard deviation increase ($\approx$ 361.8 degree days) increases less-severe physical IPV by 11.65 percentage points and injuries by 6.04 percentage points. As discussed in Section 3.4.4 and shown in Figure 7(b), these temperature patterns are associated with declines in rabi crop yields, which may partly explain the observed relationship. Further, the results in Table 4 show that the effect of cumulative degree days below 20°C on sustained injuries is positive and statistically significant only in areas where the share of cultivated area under rabi crops exceeds the national mean.

[10] District-level crop area data come from the ICRISAT District-Level Database.

Finally, as outlined in Section 3.4.2, I consider two alternative methods of determining exposure to the relevant growing season for each interviewed woman in my sample. Some IPV incidents may stem from shocks in earlier growing seasons if their harvest periods overlap with a woman's recall period for the IPV incident. For this reason, I construct weather shock measures by taking the simple average of rainfall and degree days across all growing seasons whose harvest periods overlap with the woman's 12-month IPV recall window (see Figure 4). The results, given in Table 5, show that the coefficient for drought on less-severe P-IPV increase in magnitude, while the coefficients for heat stress on IPV change minimally. Notably, the coefficients for kharif season wet shocks become statistically insignificant. Overall, these results suggest that accounting for lagged effects of weather conditions can meaningfully influence the estimated impact of weather shocks on IPV, particularly by reducing the significance of wet shocks.

Similarly, women interviewed during an ongoing growing season may be affected by contemporaneous weather conditions that shape household expectations about future crop yield. For this reason, I construct an alternate measure where I incorporate weather data from the current growing season (for women interviewed during the season, June–September), alongside past seasons falling within the recall window (see Figure 5). As reported in Table 6, I observe that with this approach, the estimated effects of drought on less-severe P-IPV and wet shock on severe P-IPV increase in magnitude, and the coefficient on cumulative degree days above 30°C increases specifically for less-severe physical IPV. Overall, these results could reflect the presence of recall bias or the influence of expectations about future crop yields.

5.2 Robustness Checks

In this subsection, I conduct an array of checks and additional tests to verify the robustness of my main results.

5.2.1 Alternate definition of rainfall shock

I test the sensitivity of my estimates by (1) applying a fitted Gamma distribution to district-level monthly rainfall and (2) using the Standard Precipitation Index (SPI) with indicators for different vingtiles of the rainfall score. The results are presented in Tables 12 and 14 of Appendix-II. In Table 12, I estimate effects across bins defined by deviations of rainfall from the long-run (1981–2012) district-level mean, normalized by the local standard deviation. The bins are set at 0.25 standard deviation intervals, using the range from –0.25 to 0 SD as the reference category. The results are broadly consistent with those reported in Table 2. As rainfall levels fall below the reference, the estimated effects on severe physical IPV and sustained injuries become larger. The driest bins show positive and significant effects, particularly for less-severe and severe physical IPV. On the wetter side, I also observe positive and significant effects across all forms of IPV, with the largest increase in severe physical IPV found in the bin defined by the range 1.5 to 1.75 SD—consistent with the wet shock effects observed in Table 2.

Table 14 presents estimates using indicators for drought and wet shocks based on percentiles derived from a fitted Gamma distribution of district-level monthly rainfall. Using this approach, I find similar patterns: drought is associated with increases in less-severe physical IPV, while wet shocks increase severe physical IPV. However, the statistical significance of the effects on sustained injuries disappears under this specification, even though the direction of the effects remains consistent.

5.2.2 Alternate temperature thresholds and non-linear effects of temperature

For my main results in Table 2, I defined the temperature threshold $t^* = 30$ when constructing the cumulative degree-day measures above and below the cutoff. In this subsection, I explore the robustness of my results by examining effect sizes across a broader range of temperature thresholds, namely from 24 to 33°C. Notably, the effect sizes remain positive across all thresholds and tend to increase as the threshold rises, thereby reinforcing my main findings. The results, presented in Figure 9 of Appendix II, plot the estimated coefficients for cumulative degree days above each threshold.

Going further, I examine the non-linear effects of temperature in both the kharif and rabi seasons by applying multiple threshold values and analyzing cumulative degree days across distinct temperature bins. For the kharif season, the 23–25°C bin serves as the reference category, while for the rabi season, the 18–20°C bin is used as the reference. The results, given in Table 13 of Appendix-II show that in the kharif season, the hottest temperature bin — defined as cumulative degree days above 31°C — has a significant and positive effect on all forms of IPV. Additionally, the 25–27°C bin also shows a positive and significant association. For the rabi season, I observe a notable increase in less-severe physical IPV within the coldest bin, defined by temperatures below 14°C. Overall, these patterns align closely with the effects reported earlier in Table 3.

5.2.3 Falsification Exercise and Effect on Urban Areas

To ensure that my estimates reflect the causal impact of exogenous weather shocks rather than unobserved, systematic determinants of IPV, I conduct a falsification exercise. Specifically, I randomly assign placebo drought and wet shock status to interviewed women across time, while keeping the district fixed. The results, presented in Table 15 of Appendix II, show no significant effects of either placebo drought or wet shocks in the kharif or rabi growing seasons.

Additionally, I estimate the main specification — focusing on the effects of weather shocks during the kharif growing season and the non-growing season — on the subsample of individuals residing in urban areas. The results, presented in Table 16, show no statistically significant effects of drought or wet shocks on IPV outcomes among urban residents. However, cumulative degree days above 30°C display a positive and statistically significant association with all forms of IPV. This suggests that while the primary pathway linking drought and wet shocks to IPV likely operates through agricultural income losses, other mechanisms related to heat stress also play a role in driving an increase in IPV, as seen in non-agricultural urban settings.

6 Mechanisms: Additional Outcomes

In this section, I explore the underlying mechanisms driving the observed increase in physical IPV among rural Indian households following weather shocks. For this analysis, I present results from my main specification that includes rainfall and temperature shocks from the main growing season (kharif), controlling for weather conditions in the non-growing season.

As documented in Section 3.4.4, drought and heat stress during the kharif season, and both heat and cold stress during the rabi season, lead to declines in crop yields. This provides evidence of an income shock that may partly explain the increase in IPV observed after these weather events.

To further probe the mechanisms outlined in Section 2.2.1, I follow Díaz and Saldarriaga (2022) by examining related outcomes that reflect poverty-induced stress (husband's alcohol use), shifts in household employment dynamics, and changes in women's financial autonomy. This allows us to disentangle between competing theories behind why IPV increases in response to climate shocks. The key results are summarized below and presented in detail in Tables 7-10.

For the kharif season, drought leads to a decline in women's financial autonomy, as measured by her control over own earnings (Table 8). Heat stress increases the likelihood of alcohol use among husbands and the likelihood of husbands exhibiting marital controlling behaviors (Table 7). With respect to labor market status, following drought, husbands shift out of agriculture and into other occupations, while wet shocks increase the likelihood that women have worked in the past year, particularly in agricultural occupations (Table 9). This pattern is consistent with higher rainfall boosting demand for female labor in India, in line with the rice-wheat dichotomy in women's employment. Higher rainfall benefits rice yield and increases demand for female labor in tasks such as weeding and transplanting (Corno, Hildebrandt and Voena, 2020; Chin, 2012). In line with this, I observe that the positive association between wet shocks and physical IPV is driven largely by these rice-growing states (Table 10).

Together, these results point to multiple mechanisms at play. Droughts in the kharif season appear to reduce women's financial autonomy, making her more vulnerable to IPV. Heat stress leads to increase in husband's alcohol consumption and marital controlling behaviours, indicating poverty induced stress. In contrast, wet shocks, especially in regions with high female agricultural labor demand, suggest a "male backlash" effect, where improvements in women's employment and autonomy threaten male gender identities, provoking violence as a means of reasserting control.

7 Heterogeneity Analysis

In this section, I examine how drought in the main growing season (June-September) influences my outcome differently depending on the impact of droughts on crop yields (through ownership of land and irrigation) or income and consumption (through access to bank account). The results are presented in Table 11.

7.1 Land ownership and Irrigation

First, I examine heterogeneity by household land ownership, using DHS survey data on whether any household member owns land, the total amount of land owned (in hectares), and the amount of that land that is irrigated. The results show that the negative effect of drought is concentrated among households without land ownership. Among land-owning households, the impact of drought is partially mitigated with each additional unit of land owned, and land owned that is irrigated.

7.2 Access to credit

Access to bank accounts — often signaling access to formal credit — may help buffer households against the adverse effects of drought on intimate partner violence (IPV) by providing a means to smooth consumption during shocks. To explore this, I examine heterogeneity based on whether the interviewed woman in my sample has a bank account, using data from the DHS survey. The results suggest that having a bank account partially mitigates the effect of drought on reported injuries from physical IPV, with the interaction effect statistically significant at the 5% level. However, it is worth noting that bank account ownership is also positively correlated with a higher overall likelihood of experiencing IPV.

8 Conclusion

This study estimates the causal effect of exposure to weather shocks during the growing season on the likelihood that women experience recent instances of physical intimate partner violence (IPV) in rural India. The main findings show that exposure to a drought during the most recent kharif season increases the prevalence of less-severe physical IPV by 11.6%, while exposure to a wet shock raises the prevalence of severe physical IPV by 30.6% compared to periods of regular rainfall. Additionally, sustained injuries from physical IPV increase following both drought and wet shocks in the kharif season, although these effects are less robust when using alternative rainfall shock definitions. Temperature extremes also matter: a one standard deviation increase in cumulative degree days above 30°C raises the prevalence of less-severe physical IPV by 14.29 % and severe IPV by 38.19%. Further analysis suggests that increased economic insecurity, men's alcohol use, marital controlling behaviors, and a decline in women's empowerment within the relationship are central pathways underlying these effects.

Leveraging the spatial heterogeneity of India's climate, I further investigate the role of income in driving these effects by separately examining shocks in the kharif and rabi seasons. Some findings align with the income loss hypothesis, such as droughts in the rabi season increasing IPV only in regions that receive relatively high rainfall during the northeast monsoon (October–December), when rabi crops are sown. Similarly, an increase in cumulative degree days below 20°C in the rabi season — which I show leads to a decline in rabi crop yields — is also associated with a rise in instances of less-severe physical IPV.

Finally, heterogeneity analyses highlight the mitigating role of household characteristics. Land ownership and access to formal banking help buffer the negative effects of drought on IPV, underscoring their importance as resilience factors. Overall, these findings point to the critical importance of prioritizing formal climate resilience initiatives to help rural households buffer against the harmful social and economic consequences of extreme weather — particularly the hidden toll on women's safety and well-being.

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9 Tables and Figures

Table 1: Descriptive Statistics

	Whole Sample (1)	Regular Rainfall (2)	Dry Shock (3)	Wet Shock (4)	Adj. Diff (2)-(3)	Adj. Diff (2)-(4)
Woman's age	33.96	33.67	33.60	34.20	0.13	-0.20
Woman's education	1.95	1.64	1.70	1.64	-0.02	0.02
Wealth	2.94	2.60	2.43	2.60	0.01	-0.05
SC/ST/OBC	0.79	0.83	0.80	0.87	0.01	0.01
Hindu	0.84	0.86	0.87	0.89	-0.01	-0.01
Presence of children under 5	0.66	0.70	0.71	0.63	0.02	0.05
Sex HH Head	1.12	1.11	1.14	1.10	0.00	-0.01
Age HH Head	45.81	45.50	45.73	45.52	0.19	0.24
Husband's education	2.50	2.28	2.33	2.26	0.04	-0.00
Marriage Year	2001.82	2001.34	2001.50	2003.41	-0.09	0.34
N	65521	28283	27165	10073		

Notes: Drought is an indicator for local rainfall levels falling below the the 30th percentile of the local historical distribution. Wetshock is an indicator for local rainfall levels falling above 80th percentile of the local historical rainfall distribution. Sample means for the whole sample of women, the sub-sample of women exposed to regular rainfall, the sub-sample of women exposed to a drought, and the sub-sample of women exposed to a wet shock during the last kharif season are reported in columns 1 through 4, respectively. Adjusted differences are obtained by regressing each variable on an indicator for exposure to a drought (column 5) or an indicator for exposure to a wet shock (column 6) and controlling for month, year, and district fixed effects. The whole sample is composed of women of reproductive age (15–49 years), who live in rural areas in India, and who live in the district for at least one year. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Climate shocks and physical IPV

	Less Severe P-IPV	Severe P-IPV	Injuries due to P-IPV
Growing Season:			
Drought	0.0288***	0.0104	0.0181***
	(0.0108)	(0.00641)	(0.00676)
Wetshock	0.0180	0.0227**	0.0177
	(0.0194)	(0.00966)	(0.0110)
Degree Days Above 30 °C	0.000414**	0.000329***	0.000178*
	(0.000178)	(0.0000977)	(0.000104)
Degree Days Below 30 °C	0.0000447	0.0000384	0.0000249
	(0.0000774)	(0.0000448)	(0.0000422)
Non-Growing Season:			
Drought	0.0204	0.00626	0.00695
	(0.0142)	(0.00800)	(0.00867)
Wetshock	0.0154	0.00845	-0.000210
	(0.0165)	(0.00836)	(0.0103)
Degree Days Above 30 °C	-0.000196	-0.000118	0.0000677
	(0.000152)	(0.0000952)	(0.0000860)
Degree Days Below 30 °C	-0.0000290	-0.0000282	0.0000324
	(0.0000725)	(0.0000398)	(0.0000402)
Observations	63616	63616	63616
Mean of Dependent Variable	0.249	0.0741	0.0775

Notes: The table shows estimates of β_1, β_2, β_3 and β_4 based on Eq. (2) in Section 4. **Growing season** refers to the kharif growing season (June-September) and **Non-growing season** refers to the months March-May. Drought is an indicator for local rainfall levels falling below the the 30th percentile of the local historical distribution. Wetshock is an indicator for local rainfall levels falling above 80th percentile of the local historical rainfall distribution. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Climate shocks and physical IPV: Second Monsoon Season

	Less Severe P-IPV	Severe P-IPV	Injuries due to P-IPV
Kharif Season:			
Drought	0.0264**	0.00914	0.0165**
	(0.0107)	(0.00627)	(0.00690)
Wetshock	0.0186	0.0231**	0.0179
	(0.0191)	(0.00961)	(0.0109)
Degree Days Above 30 °C	0.000455**	0.000329***	0.000220**
	(0.000187)	(0.000105)	(0.000107)
Degree Days Below 30 °C	-0.0000120	0.0000259	-0.0000110
	(0.0000924)	(0.0000513)	(0.0000475)
Rabi Season:			
Drought	0.0176	0.00868	0.0145*
	(0.0147)	(0.00717)	(0.00834)
Wetshock	-0.0319	-0.00225	-0.0166
	(0.0214)	(0.00988)	(0.0131)
Degree Days Above 20 °C	0.0000152	0.0000101	-0.0000465
	(0.000124)	(0.0000737)	(0.0000666)
Degree Days Below 20 °C	0.000322**	0.0000808	0.000167**
	(0.000128)	(0.0000668)	(0.0000849)
Observations	63616	63616	63616
Mean of dependent variable	0.249	0.0741	0.0775

Notes: The table presents the estimates of β_1, β_2, β_3, and β_4 from Equation (3) in Section 4, extended to include shocks from the secondary rabi growing season (October–December). In the rabi season, drought and wetshock are defined as local rainfall levels falling below the the 15th percentile and above the 85th percentile of the local historical distribution respectively. In the kharif season, drought and wetshock are defined as local rainfall levels falling below the the 30th percentile and above the 80th percentile of the local historical distribution respectively. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Rabi season shocks and physical IPV: Heterogeneity by area cultivated under rabi crops

	Less Severe P-IPV		Severe P-IPV		Injuries due to P-IPV	
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	0.0116	0.0218	0.0199*	0.00691	0.0330***	-0.00392
	(0.0220)	(0.0192)	(0.0113)	(0.0108)	(0.0123)	(0.0103)
Wetshock	-0.0202	-0.0519	0.00255	0.00618	-0.0175	-0.0132
	(0.0231)	(0.0469)	(0.0109)	(0.0191)	(0.0146)	(0.0275)
Degree Days Above 20 °C	0.000110	-0.000118	0.0000486	-0.0000848	-0.0000157	-0.0000840
	(0.000148)	(0.000196)	(0.0000871)	(0.000110)	(0.0000817)	(0.000110)
Degree Days Below 20 °C	0.000333**	0.000485**	0.0000177	0.000252**	0.000226**	0.0000663
	(0.000129)	(0.000243)	(0.0000693)	(0.000117)	(0.000112)	(0.000129)
Observations	34527	29088	34527	29088	34527	29088

Notes: The table above present estimates of the effect of exposure to drought and wetshock in the rabi growing season on IPV, across sub-samples stratified by whether the district-level long-run average area cultivated under rabi crops is greater (Column 1,3 and 5) or less (Columns 2, 4 and 6) than national mean. Drought is an indicator for local rainfall levels falling below the the 15th percentile of the local historical distribution. Wetshock is an indicator for local rainfall levels falling above 85th percentile of the local historical rainfall distribution. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The district-level data on area cultivated under different drops come from the ICRISAT District-Level Database. Weather data is sourced from the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Exploring timing: Overlapping harvest periods

	Less Severe P-IPV		Severe P-IPV		Injuries due to P-IPV	
	(1)	(2)	(3)	(4)	(5)	(6)
Previous season only:						
Drought	0.0288***		0.0104		0.0181***	
	(0.0108)		(0.00641)		(0.00676)	
Wetshock	0.0180		0.0227**		0.0177	
	(0.0194)		(0.00966)		(0.0110)	
Degree Days Above 30 °C	0.000414**		0.000329***		0.000178*	
	(0.000178)		(0.0000977)		(0.000104)	
Degree Days Below 30 °C	0.0000447		0.0000384		0.0000249	
	(0.0000774)		(0.0000448)		(0.0000422)	
Including overlapping seasons:						
Drought		0.0338***		0.0107*		0.0170**
		(0.0111)		(0.00633)		(0.00676)
Wetshock		-0.000619		0.00861		0.00327
		(0.0215)		(0.0107)		(0.0113)
Degree Days Above 30 °C		0.000395**		0.000316***		0.000143
		(0.000182)		(0.000100)		(0.000115)
Degree Days Below 30 °C		0.000127		0.0000729*		0.0000607
		(0.0000773)		(0.0000442)		(0.0000436)
Observations	63616	63616	63616	63616	63616	63616

Notes: The table presents estimates of β_1, β_2, β_3, and β_4 from Equation (3) in Section 4, focusing on the kharif season. Columns 1, 3, and 5 use the original definition of growing season exposure, while Columns 2, 4, and 6 apply an alternative definition that accounts for growing seasons whose harvest periods overlap with the interviewed woman's recall window (as illustrated in Figure 7). Here, drought is defined as an indicator for local rainfall levels falling below the 30th percentile of the historical rainfall distribution, while wet shock is defined as an indicator for rainfall levels exceeding the 80th percentile of the local historical distribution. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Exploring timing: Current weather conditions

	Less Severe P-IPV		Severe P-IPV		Injuries due to P-IPV	
	(1)	(2)	(3)	(4)	(5)	(6)
Previous season only:						
Drought	0.0288***		0.0104		0.0181***	
	(0.0108)		(0.00641)		(0.00676)	
Wetshock	0.0180		0.0227**		0.0177	
	(0.0194)		(0.00966)		(0.0110)	
Degree Days Above 30 °C	0.000414**		0.000329***		0.000178*	
	(0.000178)		(0.0000977)		(0.000104)	
Degree Days Below 30 °C	0.0000447		0.0000384		0.0000249	
	(0.0000774)		(0.0000448)		(0.0000422)	
Including current season:						
Drought		0.0399***		0.0174**		0.0181***
		(0.0115)		(0.00684)		(0.00673)
Wetshock		0.0249		0.0233**		0.0177
		(0.0204)		(0.0100)		(0.0110)
Degree Days Above 30 °C		0.000442**		0.000312***		0.000178*
		(0.000194)		(0.000104)		(0.000102)
Degree Days Below 30 °C		0.0000530		0.0000567		0.0000387
		(0.0000950)		(0.0000549)		(0.0000528)
Observations	63616	63616	63616	63616	63616	63616

Notes: The table presents estimates of β_1, β_2, β_3, and β_4 from Equation (3) in Section 4, focusing on the kharif season. Columns 1, 3, and 5 use the original definition of growing season exposure, while Columns 2, 4, and 6 apply an alternative definition that accounts for current growing season weather for women interviewed during the growing season (as illustrated in Figure 8). Here, drought is defined as an indicator for local rainfall levels falling below the 30th percentile of the historical rainfall distribution, while wet shock is defined as an indicator for rainfall levels exceeding the 80th percentile of the local historical distribution. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Mechanims: Husband's Alcohol Use and Marital Controlling Behaviours

	Drinks alcohol	Marital Control
Kharif Season:		
Drought	0.00850	0.00493
	(0.00996)	(0.0155)
Wetshock	0.0185	-0.0207
	(0.0176)	(0.0216)
Degree Days Above 30 °C	0.000324**	0.000492**
	(0.000153)	(0.000234)
Degree Days Below 30 °C	-0.000103	0.0000525
	(0.0000695)	(0.000100)
Observations	63616	63616

Notes: The table presents the estimates of β_1, β_2, β_3, and β_4 from Equation (3) in Section 4. **The outcome variables include an indicator for whether husband drinks alcohol, and an indicator for whether the husband exhibits marital controlling behaviours (is jealous if wife talks to other men, accuses wife of cheating or insists on knowing her whereabouts)**. Drought and wetshock in the kharif season are defined as local rainfall levels falling below the the 30th percentile and above the 80th percentile of the local historical distribution respectively. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Mechanims: Women's Financial Autonomy

	Woman earns more	Control over own earnings
Kharif Season:		
Drought	0.00468	-0.0291**
	(0.0158)	(0.0144)
Wetshock	0.0385	-0.00178
	(0.0307)	(0.0227)
Degree Days Above 30 °C	-0.000389	0.000197
	(0.000289)	(0.000224)
Degree Days Below 30 °C	-0.000164	-0.000101
	(0.000127)	(0.0000912)
Observations	18203	18549

Notes: The table presents the estimates of β_1, β_2, β_3, and β_4 from Equation (3) in Section 4. **The outcome variables include an indicator for whether woman earns more than her husband and whether she has control over her own earnings**. Drought and wetshock in the kharif season are defined as local rainfall levels falling below the the 30th percentile and above the 80th percentile of the local historical distribution respectively. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Mechanims: Men and Women's Employment

	Woman employed in last 12 months	Woman employed in agriculture	Husband works in agriculture
Kharif Season:			
Drought	0.0101	0.0154	-0.0318**
	(0.0112)	(0.00993)	(0.0129)
Wetshock	0.0476**	0.0361**	0.0106
	(0.0214)	(0.0175)	(0.0189)
Degree Days Above 30 °C	0.000478***	0.000282*	0.0000227
	(0.000180)	(0.000167)	(0.000198)
Degree Days Below 30 °C	-0.000258***	-0.000117	0.0000904
	(0.0000937)	(0.0000887)	(0.0000893)
Observations	63616	63616	63616

Notes: The table presents the estimates of β_1, β_2, β_3, and β_4 from Equation (3) in Section 4. **The outcome variables include an indicator variable for whether the woman was employed in the last 12 months (including both paid work and unpaid activities in family enterprises), the likelihood of her and her husband working in agricultural versus non-agricultural occupations**. Drought and wetshock in the kharif season are defined as local rainfall levels falling below the the 30th percentile and above the 80th percentile of the local historical distribution respectively. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Impact of wetshock on injuries due to P-IPV and employment: Heterogeneity by rice-growing states

	Injuries due to P-IPV		Woman employed in last 12 months		Woman employed in agriculture	
	(1)	(2)	(3)	(4)	(5)	(6)
Wetshock	0.0360**	0.0168	0.0690*	0.0325	0.0548*	0.0284
	(0.0173)	(0.0155)	(0.0411)	(0.0247)	(0.0320)	(0.0219)
Observations	25211	38403	25211	38403	25211	38403
Mean of Dependent Variable	0.288	0.223	0.0923	0.0621	0.0873	0.0711

Notes: The table above presents estimates of the effect of exposure to a wetshock in the last kharif growing season on the different forms of physical IPV, across sub-samples stratified by states classified as rice-growing (columns 1,3 and 5) and non rice-growing (columns 2, 4 and 6). The rice-growing states include Andhra Pradesh, Bihar, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Tamil Nadu and West Bengal. Wetshock is an indicator for local rainfall levels falling above 80th percentile of the local historical rainfall distribution. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Heterogenous effects of kharif season weather shocks on injuries due to P-IPV

	Outcome: Injuries due to P-IPV			
	(1)	(2)	(3)	(4)
Drought	0.0285***	0.0270***	0.0172**	0.0174**
	(0.00792)	(0.00818)	(0.00679)	(0.00678)
Drought × Bank Account	-0.0175**			
	(0.00774)			
Drought × Owns Land		-0.0165**		
		(0.00765)		
Drought × Amount Land Owned			-0.00208**	
			(0.000988)	
Drought × Amount Land Irrigated				-0.00163**
				(0.000811)
Wetshock	0.0152	0.0233*	0.0162	0.0179
	(0.0148)	(0.0135)	(0.0109)	(0.0110)
Wetshock × Bank Account	0.00264			
	(0.0125)			
Wetshock × Owns Land		-0.0102		
		(0.0120)		
Wetshock × Amount Land Owned			-0.00187	
			(0.00169)	
Wetshock × Amount Land Irrigated				-0.000480
				(0.00150)
Bank Account	0.0144***			
	(0.00491)			
Owns Land		-0.000462		
		(0.00530)		
Amount Land Owned			0.0000351	
			(0.000716)	
Amount Land Irrigated				-0.000285
				(0.000606)
Observations	63616	63616	62692	63081

Notes: The table above presents estimates for the coefficient of drought interacted with different household characteristics - which includes an indicator for whether the interviewed woman has a bank account (Bank Account), any member of the household owns land (Owns Land), the logarithm of the amount of land owned in hectares (Amount Land Owned) and the logarithm of the amount of irrigated land owned in hectares (Amount Land Irrigated). Drought is an indicator for local rainfall levels in the kharif season falling below the the 30th percentile of the local historical distribution. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Timing of Kharif rainfall and recall period of IPV

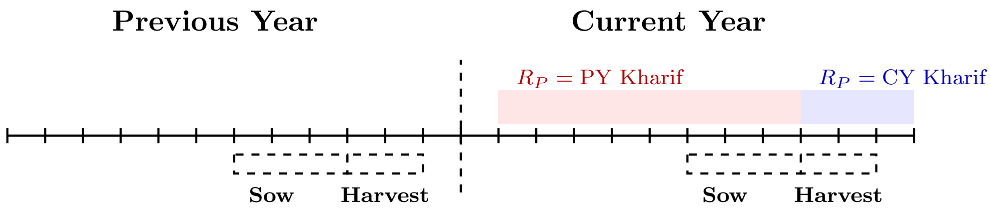


Figure 2: Timing of Rabi rainfall and recall period of IPV

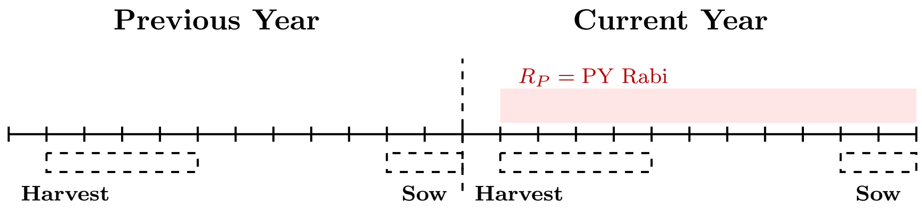


Figure 3: Monthly distribution of rainfall and temperature

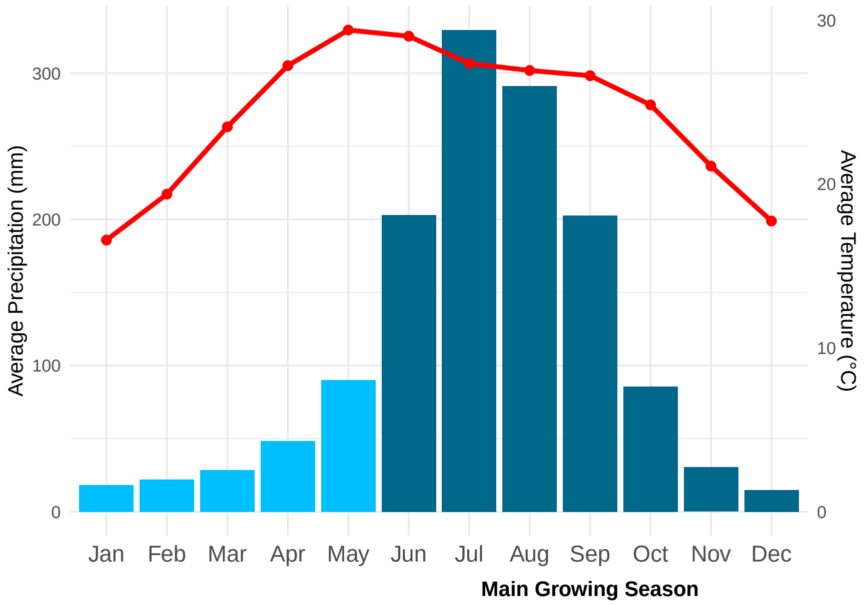


Figure 4: Alternate Timing: Accounting for seasons with overlapping harvest periods

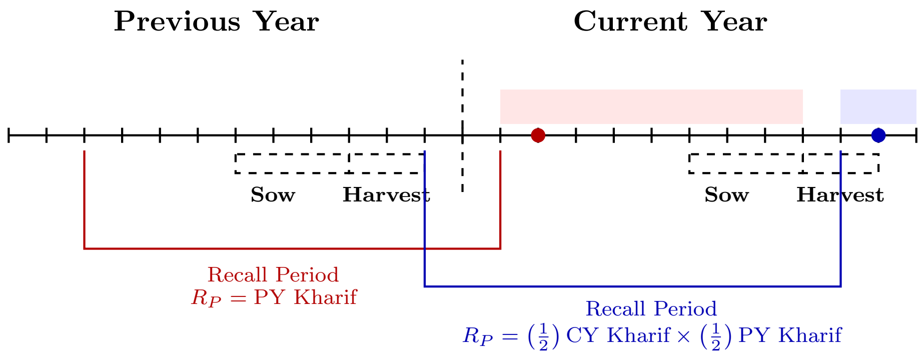


Figure 5: Alternate Timing: Accounting for current growing season period

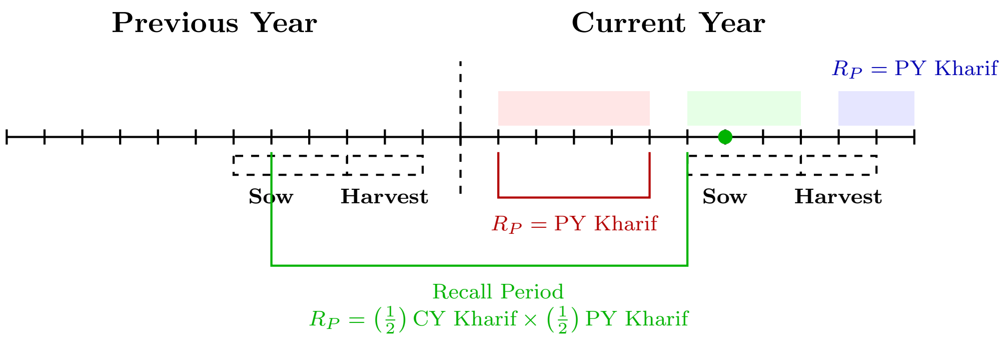
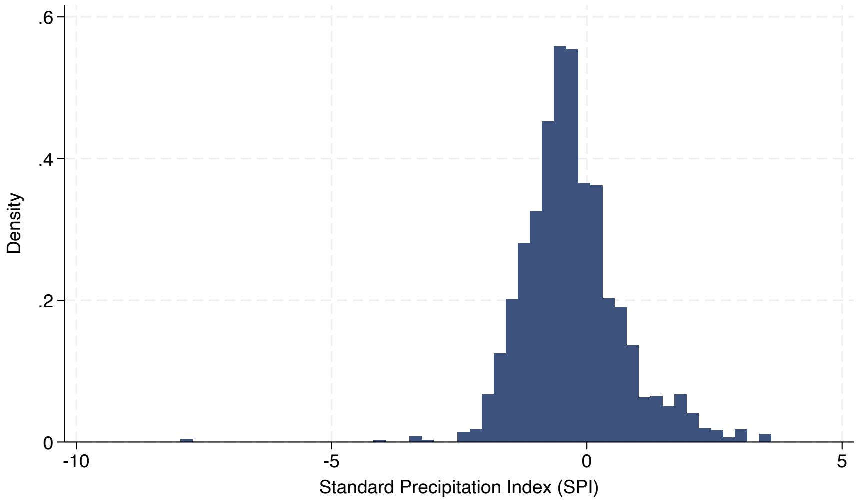
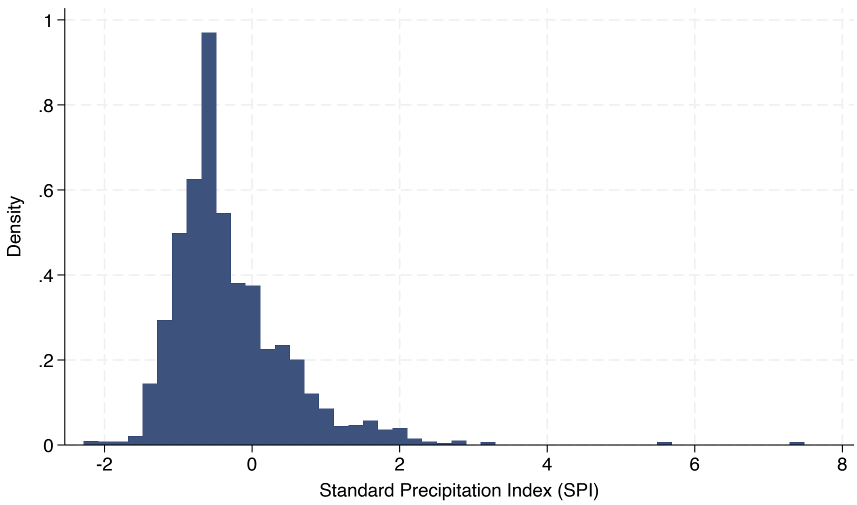


Figure 6: Standard Precipitation Index (SPI)



(a) Kharif



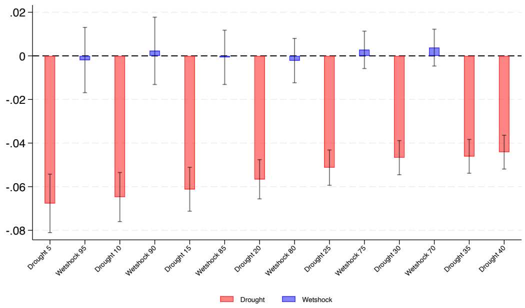
(b) Rabi

Notes: The figures above display the distribution of the Standard Precipitation Index (SPI), calculated by subtracting the long-run (1981–2012) mean rainfall from observed rainfall levels and normalizing by the local standard deviation, for the kharif (June–September) (panel a) and rabi (October–December) (panel b) growing seasons. The rainfall data are sourced from the Global Precipitation Climatology Center's (GPCC) gridded monthly precipitation series (1981–2019) and supplemented with CPC Global Unified precipitation data for 2020–2021.

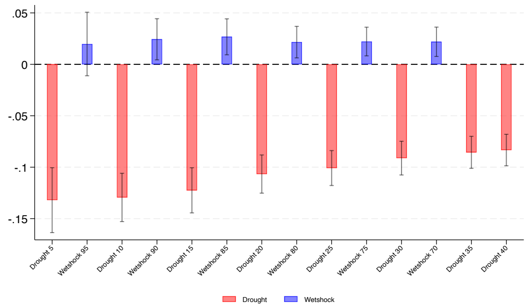
10 Appendix

10.1 Appendix-I: Additional Results

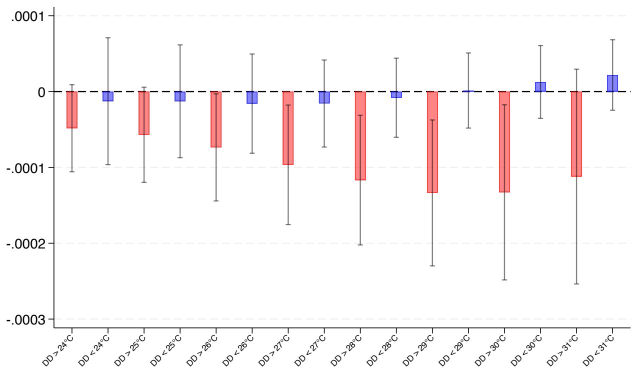
Figure 7: Kharif season climate and crop yields



(a) Rainfall shocks: All Kharif crops



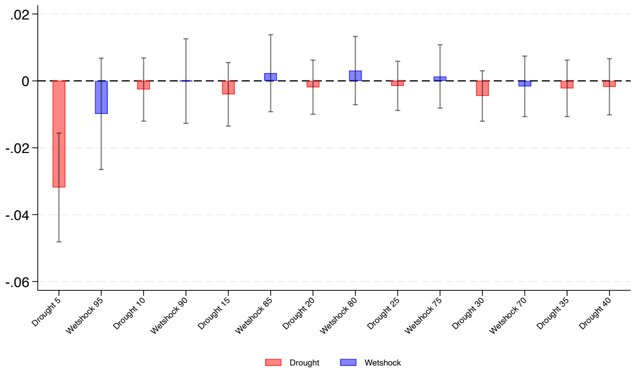
(b) Rainfall shocks: Rice



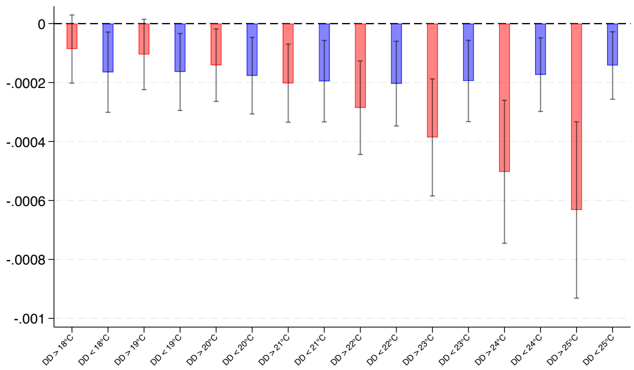
(c) Degree day thresholds: All Kharif Crops

Notes: The figures above display the coefficient estimates from a two-way fixed effects district-level panel regression of the logarithm of kharif season crop yields (production per hectare) on indicators for drought, wetshock (panels (a) and (b)) and continuous measures of cumulative degree days falling above and below different temperature thresholds (panel (c)) during the kharif growing season. Weather data is sourced from the Global Precipitation Climatology Center's (GPCC) gridded monthly precipitation series (1981–2019) and CPC Global Unified Temperature. District-level data on crop yields for the years 1980-2015 is sourced from ICRISAT District-Level Database.

Figure 8: Rabi season climate and crop yields



(a) Rainfall shocks



(b) Degree day thresholds

Notes: The figures above display the coefficient estimates from a two-way fixed effects district-level panel regression of the logarithm of rabi season crop yields (production per hectare) on indicators for drought, wetshock (panels (a) and (b)) and continuous measures of cumulative degree days falling above and below different temperature thresholds (panel (c)) during the rabi growing season. Weather data is sourced from the Global Precipitation Climatology Center's (GPCC) gridded monthly precipitation series (1981–2019) and CPC Global Unified Temperature. District-level data on crop yields for the years 1980-2015 is sourced from ICRISAT District-Level Database.

10.2 Appendix-II: Robustness Checks

Table 12: Climate shocks and physical IPV: Rainfall Bins

	Less Severe P-IPV	Severe P-IPV	Injuries due to P-IPV
Rainfall Bins:			
< -1.75 SD	0.0595*	0.0339**	0.0179
	(0.0304)	(0.0146)	(0.0162)
-1.75 to -1.5 SD	0.0642**	-0.00936	0.0106
	(0.0318)	(0.0161)	(0.0167)
-1.5 to -1.25 SD	0.0921***	0.0121	0.0300**
	(0.0290)	(0.0130)	(0.0147)
-1.25 to -1 SD	0.0557**	0.0221*	0.0293**
	(0.0256)	(0.0126)	(0.0148)
-1 to -0.75 SD	0.0585***	0.0138	0.0292**
	(0.0211)	(0.0111)	(0.0118)
-0.75 to -0.5 SD	0.0662***	0.0230*	0.0133
	(0.0243)	(0.0123)	(0.0123)
-0.5 to -0.25 SD	0.0827***	0.0230**	0.0221*
	(0.0219)	(0.0104)	(0.0113)
0 to 0.25 SD	0.0535**	0.0158	0.0252**
	(0.0259)	(0.0148)	(0.0122)
0.25 to 0.5 SD	0.0321	-0.00174	0.0297*
	(0.0287)	(0.0143)	(0.0178)
0.5 to 0.75 SD	-0.0418	-0.0264	0.000599
	(0.0359)	(0.0181)	(0.0186)
0.75 to 1 SD	0.0759**	0.0385**	0.0645***
	(0.0327)	(0.0169)	(0.0178)
1 to 1.25 SD	0.0909***	0.0226	0.0344
	(0.0336)	(0.0171)	(0.0260)
1.25 to 1.5 SD	0.00667	0.00638	-0.0148
	(0.0290)	(0.0168)	(0.0191)
1.5 to 1.75 SD	0.135***	0.0489***	0.0369*
	(0.0470)	(0.0181)	(0.0219)
> 1.75 SD	-0.00643	0.0144	0.0176
	(0.0246)	(0.0117)	(0.0132)
Observations	63616	63616	63616

Notes: The table above presents estimates from a specification where the independent variables are indicators for standardized deviations of rainfall from the long run (1981-2012) mean. Deviations in the range [-0.25,0] standard deviations of the mean are the excluded category. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Climate shocks and physical IPV: Non-linear effects of temperature

	Less Severe P-IPV	Severe P-IPV	Injuries due to P-IPV
Kharif Season:			
Degree Days < 21 °C	-0.0000541	0.0000810*	0.0000190
	(0.0000860)	(0.0000479)	(0.0000663)
Degree Days 21-23 °C	0.000122	0.000149	-0.000245
	(0.000702)	(0.000430)	(0.000545)
Degree Days 25-27 °C	0.00213***	0.000816**	0.000380
	(0.000679)	(0.000370)	(0.000326)
Degree Days 27-29 °C	0.000587	-0.0000321	0.000121
	(0.000569)	(0.000294)	(0.000318)
Degree Days 29-31 °C	0.00125*	0.000300	0.000637
	(0.000741)	(0.000371)	(0.000438)
Degree Days > 31 °C	0.000762***	0.000376**	0.000316**
	(0.000286)	(0.000148)	(0.000150)
Rabi Season:			
Degree Days < 14 °C	0.000557***	0.0000468	0.000211*
	(0.000166)	(0.0000876)	(0.000122)
Degree Days 14-16 °C	0.00278*	0.000295	0.000515
	(0.00161)	(0.000935)	(0.000933)
Degree Days 16-18 °C	0.000477	-0.0000507	-0.000721
	(0.00136)	(0.000753)	(0.000839)
Degree Days 20-22 °C	0.00113	0.000369	0.000417
	(0.00110)	(0.000541)	(0.000475)
Degree Days 22-24 °C	0.000748	-0.000356	-0.000247
	(0.000939)	(0.000574)	(0.000463)
Degree Days 24-26 °C	0.00142*	0.000666	0.0000628
	(0.000730)	(0.000419)	(0.000447)
Degree Days > 26 °C	0.000260	0.0000790	-0.000304
	(0.000438)	(0.000249)	(0.000198)
Observations	63616	63616	63616

Notes: The table presents estimates from a modified version of Equation (3) in Section 4, where the temperature effects on IPV are modeled non-linearly using cumulative degree days across distinct temperature bins. For the kharif season, the omitted reference category is 23–25°C, and for the rabi season, it is 18–20°C. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Climate shocks and physical IPV: Fitted gamma distribution

	Less Severe P-IPV	Severe P-IPV	Injuries due to P-IPV
Drought	0.0227**	0.00611	0.00266
	(0.0104)	(0.00606)	(0.00639)
Wetshock	0.0119	0.0175**	0.0122
	(0.0175)	(0.00821)	(0.00941)
Observations	63616	63616	63616
Mean of Dependent Variable	0.249	0.0741	0.0775

Notes: The table presents estimates of the effects of drought and wet shocks during the most recent kharif growing season on IPV, where the shocks are defined as indicator variables based on percentile thresholds derived from a fitted Gamma distribution of local monthly rainfall levels. Drought and wetshock are defined as local rainfall levels falling below the the 30th percentile and above the 80th percentile of the local historical distribution respectively. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Falsification Exercise: Placebo Shock

	Less Severe P-IPV	Severe P-IPV	Injuries due to P-IPV
Kharif Season:			
Drought	-0.00639	-0.000404	0.00278
	(0.00551)	(0.00369)	(0.00342)
Wetshock	-0.00941	-0.000197	-0.00298
	(0.00840)	(0.00533)	(0.00494)
Rabi Season:			
Drought	0.00398	0.00330	-0.000486
	(0.00675)	(0.00419)	(0.00444)
Wetshock	-0.000680	-0.0104*	0.00361
	(0.00969)	(0.00534)	(0.00599)
Observations	63564	63564	63564

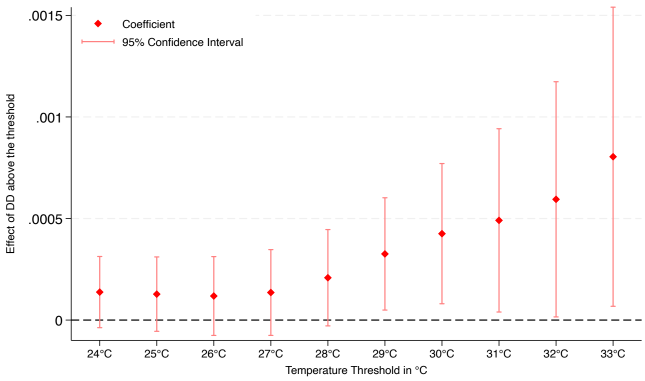
Notes: The table presents the estimates of placebo drought and wetshock in the last kharif and rabi growing seasons on IPV. Shocks are assigned randomly across time, keeping the district fixed. In the rabi season, drought and wetshock are defined as local rainfall levels falling below the the 15th percentile and above the 85th percentile of the local historical distribution respectively. In the kharif season, drought and wetshock are defined as local rainfall levels falling below the the 30th percentile and above the 80th percentile of the local historical distribution respectively. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Climate Shocks and Physical IPV: Effect on Urban Areas

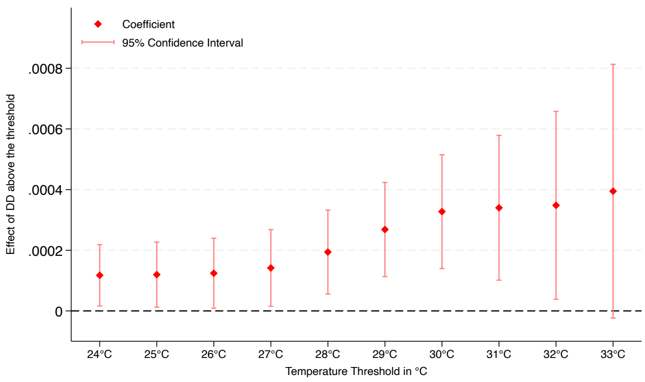
	Less Severe P-IPV	Severe P-IPV	Injuries due to P-IPV
Growing Season:			
Drought	0.0201	-0.00138	0.0155
	(0.0175)	(0.0111)	(0.0101)
Wetshock	0.0143	0.00768	0.0279**
	(0.0218)	(0.0114)	(0.0113)
Degree Days Above 30 °C	0.000724***	0.000382**	0.000365***
	(0.000273)	(0.000158)	(0.000139)
Degree Days Below 30 °C	-0.0000291	-0.00000373	-0.0000444
	(0.000112)	(0.0000602)	(0.0000593)
Non-Growing Season:			
Drought	0.00328	-0.000946	0.0168
	(0.0274)	(0.0153)	(0.0147)
Wetshock	0.0313*	0.00928	0.00499
	(0.0186)	(0.00951)	(0.0116)
Degree Days Above 30 °C	-0.000511**	-0.000169	0.0000344
	(0.000219)	(0.000113)	(0.000122)
Degree Days Below 30 °C	-0.0000276	0.0000476	0.0000406
	(0.000113)	(0.0000674)	(0.0000564)
Observations	23399	23399	23399

Notes: The table shows estimates of β_1, β_2, β_3 and β_4 based on Eq. (2) in Section 4 **on the sub-sample of women residing in urban areas**. **Growing season** refers to the kharif growing season (June-September) and **Non-growing season** refers to the months March-May. Drought is an indicator for local rainfall levels falling below the the 30th percentile of the local historical distribution. Wetshock is an indicator for local rainfall levels falling above 80th percentile of the local historical rainfall distribution. All regressions include district, month and year of interview fixed effects and are weighted using DHS sampling weights. Standard errors are given in parentheses and clustered at the district-level. The data come from the 2015-16 and 2019-21 Indian DHS, the Global Precipitation Climatology Center's (GPCC) gridded monthly time series of precipitation data (1981-2019) and CPC Global Unified temperature (2015-2021) and precipitation data (2020-2021).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

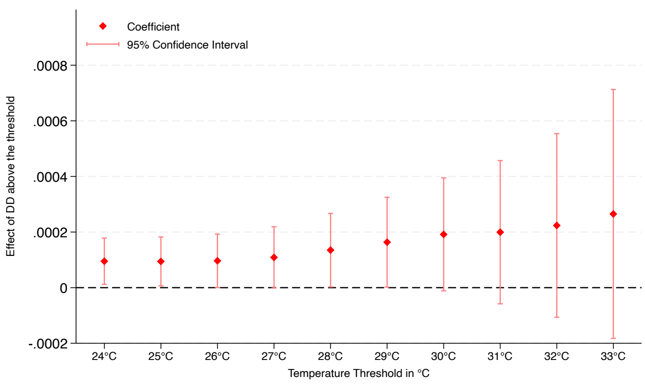
Figure 9: Temperature threshold effects on different IPV outcomes



(a) Less Severe Physical Violence



(b) Severe Physical Violence



(c) Injuries from Physical Violence