RESEARCH ARTICLE

Does drought increase intimate partner violence? Evidence from India

Durgesh C. Pathak* and **Dipti Chhugani**

Department of Economics and Finance, Birla Institute of Technology and Science Pilani, Hyderabad Campus, Hyderabad, Telangana, India

Abstract

India has a high prevalence of intimate partner violence (IPV) against women. IPV has been observed to increase during natural disasters. Many studies have attempted to unravel the effect of drought on IPV; however, the evidence remains mixed. There is a gap in such studies in the Indian context, and this study seeks to fill this gap. We used data from the National Family Health Survey-4 (NFHS-4) (2015 – 2016) and NFHS-5 (2019 – 2021) to examine the effect of drought caused by the failure of the northeastern monsoon (NEM) in 2016 – 2018. Our analysis included data from 19 states and Union Territories of India (N = 34,590) in a difference-in-differences setup to evaluate the effect of the NEM drought on IPV. Exposure to the NEM drought was positively associated with physical violence (PV) and emotional violence, with results significant at the 95% and 99% confidence levels, respectively. A subsample analysis of rural and urban populations revealed that drought is significantly associated with an increase in sexual violence in urban areas, whereas it correlates with PV in rural areas. Additionally, exposure to drought is linked to a considerable rise in the controlling behavior of partners, for example, "He (is/was) jealous or angry if you (talk/talked) to other men,""he (does/did) not permit you to meet your female friends."These findings call for a two-fold policy action: providing support in the form of wage employment programs, subsidies, and other financial assistance during drought periods to help households cope with financial stress and implementing awareness programs aimed at changing partners' mindsets, thereby reducing controlling behaviors in marriages.

Keywords: Drought; India; Intimate partner violence; National family health survey

1. Introduction

Natural disasters and extreme events have impacted human lives in several ways throughout history. As the effects of climate change become more pronounced, the intersection of environmental stressors and social issues has become an increasingly important area of study. One critical aspect of this intersection is the relation between drought and intimate partner violence (IPV). Droughts, characterized by prolonged periods of insufficient rainfall, have far-reaching consequences beyond immediate agricultural and economic impacts. Imagine living through a drought: crops fail, income drops, water becomes scarce, and stress builds as families worry about their next meal and how to make ends meet. This heightened stress does not stay confined to the fields; it seeps into homes, affecting relationships and mental health and potentially leading

to increased IPV, where the strain and pressure of tough times can escalate household conflicts.

Declining agricultural output due to drought may lead to economic distress and food insecurity, which can intensify IPV toward women. One channel for this increased violence is reduced family income from crop failure. Although research on the association between drought and IPV is scarce globally and specifically within India, studies like those by Cools *et al.* (2020), Epstein *et al.* (2020), and Cooper *et al.* (2021) have explored the relation in various African countries. However, the evidence remains mixed. To the best of our knowledge, only Rai *et al.* (2021) have examined the effects of drought on IPV among Indian women. However, they acknowledge limitations in their data collection, as it coincided with the drought, potentially biasing their results. Our study seeks to address this gap using a dataset free from such timing issues.

Drought may affect IPV differently across population groups. Rural households, which rely heavily on agriculture than urban households, are likely to experience income reductions both directly, due to crop failure, and indirectly, from fewer farm-employment opportunities. This economic stress, a known contributor to IPV, can disproportionally affect rural households. However, no research to date has investigated the heterogeneous effect of drought on IPV in rural and urban populations. Our study aims to fill this gap.

Although IPV is a global issue, affecting approximately 30% of women worldwide, the IPV rate in Southeast Asia prevails at 37.7% (WHO, 2013). In India, the National Family Health Survey-5 (NFHS-5) shows that around 32% of women aged 18 – 49 have experienced either physical violence (PV) or sexual violence (SV) by their intimate partner (International Institute for Population Sciences & ICF, 2021). Several Indian states experienced severe drought between 2016 and 2018. The data collection period for the NFHS-5 aligns with the recall period for IPV questions in the Demographic and Health Survey (DHS) questionnaire, providing a unique opportunity to study the effects of drought on IPV in a natural experiment setting. Using difference-in-difference (DID) estimates, we analyze the impact of drought on IPV in Indian women. Our study adds to the literature on IPV with robust results and indicates a causal relation between drought and IPV.

1.1. Literature review

Human history has been interspersed with natural disasters. One such disaster is drought, which is caused by rainfall shortages. India receives its annual rainfall during two primary monsoon seasons: the Indian summer monsoon (southwestern monsoon [SWM]), which occurs from July to September, and the Indian winter monsoon (northeastern monsoon [NEM]), which spans from October to December (Mishra *et al.*, 2021). Although India receives the majority of its annual rainfall from the SWM, the NEM, which is crucial for the southern peninsular states, contributes to 11% of India's annual rainfall, with several districts in the southern peninsula receiving about 30 – 60% of their yearly rainfall during this period (Rajeevan *et al.*, 2012). On average, the NEM accounts for more than 40% of the region's total annual rainfall (Mishra *et al.*, 2021).

1.1.1. Monsoon and the Indian economy

Gadgil and Gadgil (2006) examined the impact of monsoon variability on India's gross domestic product (GDP) and agriculture, finding that a deficit in rainfall affects GDP more significantly than surplus rainfall. The NEM shows higher variability than the SWM, and a substantial decrease in agricultural output is observed in the southern peninsula during the NEM-deficit year (Rajeevan *et al.*, 2012). For instance, data from the Directorate of Economics and Statistics of the Government of India (GOI, 2020) reveal that rabi food grains yield in Andhra Pradesh dropped to 2623 kg/ha in 2018 – 2019, compared to 3086 kg/ha in 2017 – 2018 and 3284 kg/ha in 2019 – 2020. Similarly, in Karnataka, the yield dropped to 931 kg/ha in 2018 – 2019, down from 1114 kg/ha in 2017 – 2018 and 1344 kg/ha in 2019 – 2020. However, the all-India average food grain production for rabi increased in 2018 – 2019, indicating that states affected by an NEM precipitation deficit experienced a decline in rabi food grain production.

1.1.2. Natural disasters and women

O'Keefe *et al.* (1976) argue that "disaster occurs at the interface between extreme physical phenomena and vulnerable human populations," emphasizing the importance of recognizing both elements. Disaster vulnerability theory explains why certain individuals, groups, or communities experience greater losses during disasters (Zakour & Gillespie, 2012). Both physical and social factors contribute to disaster vulnerability. It is crucial to understand how natural events (physical factors) and economic, political, and cultural factors (social factors) influence vulnerability to disasters (Zakour & Gillespie, 2012).

Women often experienced increased vulnerability during disasters. Thurston *et al.* (2021) discussed the increased risk that women and girls face amidst natural hazards and disasters. For example, Weitzman and Behrman (2016) analyzed IPV before and after the 2010 Haiti earthquake using data from the DHS and found that

exposure to the earthquake's devastation increased the likelihood of both physical and sexual IPV. In India, Sekhri and Storeygard (2014) found that deviations in annual rainfall by one standard deviation from the local average led to a 7.8% increase in dowry deaths, whereas wet shocks had no noticeable effect. Sahni and Sinha (2018) reported that communities experiencing higher-than-average annual precipitation were less likely to report IPV. Rao (2020) examined IPV in Andhra Pradesh, Tamil Nadu, Karnataka, and Kerala before and after the 2004 Indian Ocean tsunami and found a correlation between being affected by the tsunami and IPV.

1.1.3. Drought and IPV

Research on the relationship between drought and IPV has offered mixed results. Epstein *et al.* (2020) analyzed cross-sectional surveys of 83,990 women from 19 sub-Saharan African countries between 2011 and 2018, finding that several droughts were associated with a higher risk of reporting PV, SV, or emotional violence (EV). However, they did not find a connection between drought and partners' controlling behavior. Cools *et al.* (2020) used DHSs from 17 sub-Saharan countries between 2003 and 2013 to study the effects of rainfall shocks on IPV, concluding that there was no significant association. Unlike Epstein *et al.* (2020), Cools *et al.* (2020) controlled for spatial correlations. Cooper *et al.* (2021) attempted to reconcile these contradictory findings by combining the methodologies of both studies. Although their sample size was larger, including DHSs from sub-Saharan Africa, Latin America, and Asia, they found insignificant relation between drought and IPV on any of the three continents. However, Rai *et al.* (2021) examined the effect of cyclones and drought on IPV among Indian women and found no statistically significant association between drought and IPV, although a positive correlation was noted between drought and PV.

1.2. Research purpose

After reviewing the existing literature on IPV, we realized that the debate surrounding the association between droughts and IPV remains open, with mixed evidence at best. Several attempts have been made to establish a statistically significant association between rainfall shocks and IPV using large sample sizes (Cools *et al.*, 2020; Cooper *et al.*, 2021; Epstein *et al.*, 2020) while controlling for known individual- and household-level covariates of IPV (Cooper *et al.*, 2021; Epstein *et al.*, 2020), as well as spatial correlations (Cools *et al.*, 2020; Cooper *et al.*, 2021). We employed a slightly different approach. First, we focused on data only from Indian states to avoid cultural and contextual differences that might affect the results.

Second, only a few studies have analyzed the effect of drought on IPV within the Indian context. Rai *et al.* (2021) examined the effects of drought and cyclones on IPV among Indian women and found a positive association between exposure to cyclones and all forms of IPV, but no such relationship was observed between drought exposure and IPV. However, the data collection period in their study coincided with the drought period; thus, the result may not fully reflect the effects of drought. Our study overcomes this limitation. Third, we used subsample analysis to understand the heterogeneous effects of drought on rural and urban sectors. Fourth, we benefited from conducting a DHS just before the NEM drought and a second DHS after the drought. The question about IPV refers to incidences within the last 12 months, aligning with the data collection time of the second survey and the NEM drought. Unlike nationwide droughts, exposure to the NEM drought was localized; thus, we did not account for spatial correlation. In addition, we used drought as a binary variable rather than employing actual rainfall deficiency data across districts. Districts are smaller units compared to states or countries, and rainfall deficiency is more uniform in smaller geographical areas. We also used district-level fixed effects to control for unobserved heterogeneities and clustered the standard errors at the district level.

Moreover, this study improves on previous studies by incorporating an extensive set of control variables, which allows for more precise estimates of the drought's effect. Thus, the objective of this study is to isolate the impact of drought on different forms of IPV.

South India experienced an extreme NEM drought from 2016 to 2018 (Mishra *et al.*, 2021). This drought was the worst in the past 150 years, with a precipitation deficit of 45%. As a result, four of Chennai's reservoirs dried up, leading to the declaration of a "Day Zero" in the summer of 2019 (Jain, 2021). As the drought occurred and affected lives before the NFHS-5 data collection and the recall period for IPV questions coincides with the drought period, this situation creates a natural experiment. Therefore, the data should capture the effect of drought on IPV. Although the data are not longitudinal, which makes it technically difficult to establish a causal relationship between drought and IPV, one thing is certain: the relation is not bidirectional; incidences of IPV cannot cause drought.

2. Data and methods

DHSs are nationally representative household surveys that collect population, health, and nutrition data across regions, including sub-Saharan Africa, North Africa/West Asia/Europe, Central Asia, South and Southeast Asia,

Oceania, Latin America, and the Caribbean. There are two types of DHSs: the Standard DHS, conducted every 5 years with a large sample size to allow for time-based comparison, and the Interim DHS, conducted between the standard DHSs, using a smaller questionnaire and sample size. The DHSs for India are also referred to as the NFHS. For consistency, the term NFHS was used in this study. We used pooled data from NFHS-4 (DHS-2015 – 2016) and NFHS-5 (DHS-2019 – 2021). Data collection for NFHS-4 occurred in two phases (January 20, 2015 – December 04, 2016), and for NFHS-5, it was conducted in two phases: Phase 1 from June 17, 2019 to January 30, 2020, and Phase 2 from January 02, 2020, to April 30, 2021. In total, NFHS-4 interviewed 699,686 women and 112,122 men from 601,509 households, and NFHS-5 interviewed 724,115 women and 101,839 men from 636,699 households.

The Couples' recode file, which contains 63,696 observations from NFHS-4 and 57,535 observations from NFHS-5, is used in this analysis. Of these, 47,514 women in NFHS-4 and 46,353 women in NFHS-5 were interviewed for the domestic violence module. Table S1 summarizes this information.

The domestic violence module of NFHS-5 was administered to women aged 18 – 49 years in a subsample of households selected for the state module, following a similar structure as that of NFHS-4. According to the World Health Organization guidelines on the ethical collection of domestic violence data, only one eligible woman per household was randomly selected. The module was not administered if privacy could not be obtained after at least three attempts to ensure respondent confidentiality.

For comparability, Dadra and Nagar Haveli and Daman and Diu were combined in the NFHS-4 sample, as NFHS-5 represents these Union Territories. As NFHS-4 did not collect data for Ladakh, we excluded this region from NFHS-5.

The onset of the COVID-19 pandemic interrupted the data collection process. Data for 16 states were collected in 2019 (Table S2) and completed by February 2020 in the Andaman and Nicobar Islands and Lakshadweep. For the remaining states and Union Territories, the data were collected between 2020 and 2021. We used data from 19 states and Union Territories, for which the data collection was completed in February 2020. The states and Union Territories included in the analysis are marked with an asterisk in Table S2.

Due to the legal obligations of the Protection of Children from Sexual Offenses Act, we included only respondents aged 18 years or older. We also excluded observations with missing values for covariates and cases in which the value of the variable "d121" (whether the respondent had seen her father beat her mother) was 8, as well as observations with missing values for "s116" (the respondent's social group). The final sample size comprises 34,590 observations, with 16,123 from NFHS-4 and 18,467 from NFHS-5.

2.1. Dependent variable

IPV can take various forms. The NFHS measures three forms of IPV PV, SV, and EV. A woman is considered to have experienced PV if, in the past 12 months, her intimate partner has pushed, shook, slapped, punched, kicked, dragged, strangled, or burned her, twisted her arm, or threatened her with a knife. SV occurs when a woman is forced into unwanted sexual activities or acts by her partner. EV includes humiliation, insults, threats of harm, or other forms of emotional abuse. Each form of IPV is measured as a dichotomous variable and takes the value of 1 if the woman has experienced it at any time or in the past 12 months, and 0 otherwise.

2.2. Independent variables

The independent variable in this study explains the effect of drought on IPV. The Indian states of Andhra Pradesh, Karnataka, and Tamil Nadu experienced severe droughts in 2018 due to a precipitation deficit from NEM. However, because data collection in Tamil Nadu was interrupted by COVID-19, we excluded Tamil Nadu and similar states and Union Territories. This left Andhra Pradesh and Karnataka as the two states exposed to NEM drought. We created a binary variable, "Drought," by coding districts in drought-affected states as 1 and districts in unaffected states as 0. Thus, all districts in Andhra Pradesh and Karnataka are coded as 1 to proxy for drought exposure from the NEM. In impact evaluation terms, Andhra Pradesh and Karnataka represent the treatment group, and the remaining 16 states and Union Territories represent the comparison group.

2.3. Control variables

The primary source of our control variables was covariates commonly recognized in the IPV literature (Dhanaraj & Mahambare, 2021; Pathak, 2022; Pathak & Kumar, 2023). We controlled the respondent-level characteristics, including current age (a categorical variable with seven categories), education level of both the respondent and her partner (a categorical variable with six categories), age at first cohabitation, age at first childbirth, total number of children born, and respondent's employment status. In addition, we controlled for whether the respondent had witnessed her father beating her mother.

We also incorporated the degree of autonomy enjoyed by respondents, measured by the women's autonomy index. DHSs ask whether women have a say in various decision-making processes. A response of "yes" is coded as 1, and "no" is coded as 0. The autonomy index is the sum of these responses, ranging from 0 to 6. The higher the score, the greater the respondent's autonomy in household decisions. Another control variable used is the number of control issues faced by the respondent, as reported by the DHS. This variable also ranges from 0 to 6, with a higher score indicating a more controlling partner.

We controlled for the partner's current age (a categorical variable with eight categories), education level, and alcohol consumption. In addition, we controlled for household-level characteristics, including the respondent's religion (Hindu, Muslim, or Others), social group, household size, urban residence, urban area, and household wealth index. The household wealth index is a composite measure of a household's cumulative living standard, reflecting ownership of various consumer items, such as television, housing type, toilet facilities, and drinking water sources. The wealth index categorizes households into five groups: poorest, poorer, middle, richer, and richest.

DHSs are cross-sectional in nature. Although we do not know whether the same households or clusters were repeated across the two survey rounds, we know that the sample is drawn from each district, meaning that the districts are repeated. We used this information to include district-level fixed effects and cluster standard errors at the district level in all models.

2.4. Study design

The occurrence of NEM droughts in only some Indian states makes this study a natural experiment. Our study follows a "pre–post, with–without" design. The states that were exposed to NEM drought were compared with those that were not. This creates the "with" and "without" groups. The data are drawn from 2 time points: 2015 – 2016 and 2019 – 2021. As there was no NEM drought in 2015 – 2016, this period is labeled "Pre" (pre-exposure to drought), whereas data for 2019 – 2021 represents "Post" (post-exposure to drought).

We adopted natural experiment terminology to describe our groups, referring to the 2015 – 2016 data (from NFHS-4) as "pre" and the 2019 – 2021 data (from NFHS-5) as "post." States not exposed to the NEM drought served as the "comparison group," whereas those exposed (Andhra Pradesh and Karnataka) were the "treatment group."

2.5. Statistical analysis

We analyzed the associations between the variables using the proportions test, Chi-square tests, Goodman and Kruskal's gamma, Kendall's tau-b test, Cramer's V test, and kernel density plots. Furthermore, the DID technique, along with logistic regressions, was employed to estimate the effect of drought on IPV. All statistical analyses were conducted using Stata 18.

2.6. Estimated model

We estimated the following model:

$$O_{it}=\beta_0+\beta_1\,Year_i+\beta_2\,drought_{it}+\beta_3\,(Year_{it}*drought_{it})+\beta_4\,C_{it}+\epsilon_{it}$$

Where O_{it} represents the log odds of a woman facing IPV in time t, $year_{it}$ is a binary variable, taking the value 0 of observation from NFHS-4 (2015 – 2016) and 1 for NFHS-5 (2019 – 2021), $drought_{it}$ is a binary variable coded as 1 for states experiencing the 2018 drought and 0 for the rest of the states, and C_{it} represents a vector of control variables.

The main coefficient of interest is β_3, which captures the interaction between the year and drought. This coefficient reflects the drought's impact on IPV, estimated using the DID approach. ϵ represents the error term.

3. Results

We first present the descriptive statistics of the study sample in Table 1. We then proceed to examine the similarities and differences in the incidence of IPV between the treatment and comparison groups. In addition, we analyze how these two groups have fared over time in terms of IPV incidence (Table 2).

Next, we explored the change in the controlling behavior of partners over time and analyzed the association between control issues faced by the respondents and the incidence of IPV. Figure 1A-C illustrate these findings. Finally, we estimate the effect of the NEM drought on IPV (Table 3 and Figure 2).

We also conducted a subsample analysis by examining urban and rural samples (Table 4). The results align with our main findings. To verify the robustness of the estimates, we perform falsification tests by modifying the drought timeline (Table S7). These results confirm that drought significantly affects IPV, and our main findings are not mechanical.

3.1. Descriptive statistics

Table 1 presents the descriptive statistics of the study sample. The total number of observations for 2015 – 2016 is 13,908 in the comparison group and 2215 in the treatment

Table 1. Sociodemographic profile of the sample[a]

	Pre (2015 – 2016)		Post (2019 – 2021)	
	Comparison	Treatment	Comparison	Treatment
Individual level variables				
Age of the respondent				
15 – 19[b]	309 (2.22)	55 (2.48)	269 (1.71)	47 (1.73)
20 – 24	1,838 (13.22)	297 (13.41)	1,761 (11.19)	278 (10.21)
25 – 29	3,067 (22.05)	502 (22.66)	3,215 (20.42)	560 (20.57)
30 – 34	2,969 (21.35)	508 (22.93)	3,364 (21.37)	595 (21.85)
35 – 39	2,684 (19.30)	407 (18.37)	3,294 (20.92)	589 (21.63)
40 – 44	1,876 (13.49)	282 (12.73)	2,254 (14.32)	388 (14.25)
45 – 49	1,165 (8.38)	164 (7.4)	1,587 (10.08)	266 (9.77)
Age of the partner				
15 – 19[b]	27 (0.19)	1 (0.05)	23 (0.15)	1 (0.04)
20 – 24	607 (4.36)	56 (2.53)	556 (3.53)	21 (0.77)
25 – 29	1,837 (13.21)	242 (10.93)	1,815 (11.53)	211 (7.75)
30 – 34	2,717 (19.54)	421 (19.01)	2,813 (17.87)	448 (16.45)
35 – 39	2,969 (21.35)	468 (21.13)	3,396 (21.57)	618 (22.7)
40 – 44	2,378 (17.10)	419 (18.92)	2,831 (17.98)	519 (19.06)
45 – 49	2,096 (15.07)	337 (15.21)	2,647 (16.81)	533 (19.57)
50 – 54	1,277 (9.18)	271 (12.23)	1,663 (10.56)	372 (13.66)
Education of the respondent				
No education	3,528 (25.37)	655 (29.57)	3,787 (24.05)	736 (27.03)
Incomplete primary	1,293 (9.30)	177 (7.99)	2,256 (14.33)	337 (12.38)
Complete primary	727 (5.23)	162 (7.31)	NA	NA
Incomplete secondary	5,964 (42.88)	890 (40.18)	7,901 (50.18)	1,338 (49.14)
Complete secondary	1,110 (7.98)	156 (7.04)	321 (2.04)	55 (2.02)
Higher	1,286 (9.25)	175 (7.9)	1,479 (9.39)	257 (9.44)
Education of the partner				
No education	2,085 (14.99)	508 (22.93)	2,562 (16.27)	580 (21.3)
Incomplete primary	1,489 (10.71)	226 (10.2)	2,426 (15.41)	456 (16.75)
Complete primary[c]	755 (5.43)	159 (7.18)	NA	NA
Incomplete secondary	6,486 (46.64)	857 (38.69)	8,360 (53.10)	1,287 (47.26)
Complete secondary	1,340 (9.63)	191 (8.62)	403 (2.56)	56 (2.06)
Higher	1,753 (12.6)	274 (12.37)	1,993 (12.66)	344 (12.63)
Age at first cohabitation				
Mean	19.27	18.16	19.12	18.53
Median	19	18	18	18
Age at first childbirth				
Mean	21.0561	20.0342	20.8840	20.3534
Median	20	20	20	20
Number of children ever born				
Mean	2.44	2.10	2.38	2.10
Median	2	2	2	2

(Contd...)

Table 1. (*Continued*)

	Pre (2015 – 2016)		Post (2019 – 2021)	
	Comparison	Treatment	Comparison	Treatment
Respondent currently working				
No	10,072 (72.42)	1,543 (69.66)	10,495 (66.66)	1,547 (56.81)
Yes	3,836 (27.58)	672 (30.34)	5,249 (33.34)	1,176 (43.19)
Partner drinks alcohol				
No	9,534 (68.55)	1,594 (71.96)	11,264 (71.54)	2,021 (74.22)
Yes	4,374 (31.45)	621 (28.04)	4,480 (28.46)	702 (25.78)
History (has the respondent seen her father ever beat her mother?)				
No	11,395 (81.93)	1,577 (71.2)	12,927 (82.11)	1,785 (65.55)
Yes	2,513 (18.07)	638 (28.8)	2,817 (17.89)	938 (34.45)
Number of control issues reported				
0	8,004 (57.55)	1,348 (60.86)	9,226 (58.60)	1,505 (55.27)
1	2,292 (16.48)	471 (21.26)	2,687 (17.07)	391 (14.36)
2	1,512 (10.87)	146 (6.59)	1,627 (10.33)	249 (9.14)
3	896 (6.44)	118 (5.33)	1,017 (6.46)	213 (7.82)
4	693 (4.98)	64 (2.89)	574 (3.65)	127 (4.66)
5	330 (2.37)	26 (1.17)	314 (1.99)	80 (2.94)
6	181 (1.3)	42 (1.9)	299 (1.9)	158 (5.8)
Mean	0.97	0.79	0.93	1.24
Median	0	0	0	0
Woman autonomy index				
0	1,589 (11.43)	390 (17.61)	1277 (8.11)	429 (15.75)
1	753 (5.41)	156 (7.04)	719 (4.57)	161 (5.91)
2	1,123 (8.07)	244 (11.02)	1221 (7.76)	257 (9.44)
3	1,825 (13.12)	300 (13.54)	1,956 (12.42)	375 (13.77)
4	8,618 (61.96)	1,125 (50.79)	10,571 (67.14)	1,501 (55.12)
Household variables				
Social group				
Scheduled caste	1,703 (12.75)	439 (21.15)	2,232 (15.42)	570 (21.39)
Scheduled tribe	3,650 (27.33)	199 (9.59)	4,151 (28.67)	224 (8.41)
Other backward castes	4,886 (36.59)	1,134 (54.62)	5,672 (39.18)	1,593 (59.77)
None of them	3,034 (22.72)	298 (14.35)	2,343 (16.18)	274 (10.28)
Don't know	80 (0.60)	6 (0.29)	79 (0.55)	4 (0.15)
Religion				
Hindu	9,424 (67.76)	1,866 (84.24)	10,899 (69.23)	2,351 (86.34)
Muslim	1,573 (11.31)	268 (12.10)	1,992 (12.65)	279 (10.25)
Others	2,911 (20.93)	81 (3.66)	2,853 (18.12)	93 (3.42)
Number of household members				
Mean	5.0724	4.8321	4.8443	4.7268
Median	5	4	5	4
Wealth index				
Poorest	2,329 (16.75)	125 (5.64)	3,475 (22.07)	167 (6.13)
Poorer	3,143 (22.60)	475 (21.44)	3,870 (24.58)	513 (18.84)

(Contd...)

Table 1. (*Continued***)**

	Pre (2015 – 2016)		Post (2019 – 2021)	
	Comparison	Treatment	Comparison	Treatment
Middle	3,126 (22.48)	663 (29.93)	3,454 (21.94)	907 (33.31)
Richer	3,031 (21.79)	626 (28.26)	3,014 (19.14)	734 (26.96)
Richest	2,279 (16.39)	326 (14.72)	1,931 (12.26)	402 (14.76)
Residence place				
Urban	4,228 (30.40)	749 (33.81)	3,766 (23.92)	766 (28.13)
Rural	9,680 (69.60)	1,466 (66.19)	11,978 (76.08)	1,957 (71.87)
Total	13,908 (100)	2,215 (100)	15,744 (100)	2,723 (100)

Notes: [a]Column-wise percentages are given in parentheses. [b]NFHS has not reported data for individuals below 17 years old due to the provisions of the POCSO Act. Though we used the predefined age groups, the 15 – 19 age groups contains no observation below 18. [c]Data for 2019 – 2020 does not include information for this category.
Source: Authors' computations using unit-level data from NFHS-4 and NFHS-5.

Table 2. Incidence of IPV in the treatment and comparison groups and its change

Group	Physical violence (proportion)			Sexual violence (proportion)			Emotional violence (proportion)		
	Pre (t_0)	Post (t_1)	Change over time ($t_1 - t_0$)	Pre (t_0)	Post (t_1)	Change over time ($t_1 - t_0$)	Pre (t_0)	Post (t_1)	Change over time ($t_1 - t_0$)
Comparison (C)	0.2542	0.2592	0.0050	0.0624	0.0483	−0.0141***	0.1193	0.1199	0.0006
Treatment (T)	0.2709	0.3970	0.1261***	0.0537	0.0834	0.0296***	0.1278	0.2174	0.0896***
Difference between groups ($T - C$)	0.0166*	0.1378***		−0.0087	0.0350***		0.0085	0.0975***	

Note: ***$p<0.01$, **$p<0.05$, *$p<0.1$.
Source: Authors' computation using unit-level data from NFHS-4 and NFHS-5.

Table 3. DID estimation results

	Model with no controls			Model with complete controls		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	PV	SV	EV	PV	SV	EV
Year	0.985	0.747***	0.934	1.103	0.850	1.019
	(0.0644)	(0.0758)	(0.0758)	(0.0755)	(0.0949)	(0.0849)
Drought: yes (Base: no)	0.915	0.281***	0.419***	1.872***	0.550***	1.028
	(0.0826)	(0.0284)	(0.0362)	(0.197)	(0.0769)	(0.113)
Year*Drought	1.828***	2.140***	2.029***	1.475**	1.247	1.442***
	(0.335)	(0.409)	(0.315)	(0.283)	(0.247)	(0.203)
Respondent-level controls	N	N	N	Y	Y	Y
Partner level controls	N	N	N	Y	Y	Y
Household-level controls	N	N	N	Y	Y	Y
District fixed effects	Y	Y	Y	Y	Y	Y
Constant	0.456***	0.0936***	0.184***	0.184**	0.0204***	0.188***
	(0.0149)	(0.00416)	(0.00728)	(0.130)	(0.00828)	(0.110)
Pseudo R^2	0.0944	0.0736	0.0569	0.2402	0.2274	0.2324
Observations	34,590	33,233	34,153	30,100	28,635	29,597

Notes: Robust standard errors in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$.
Source: Authors' computation using unit-level data from NFHS-4 and NFHS-5.
Abbreviations: PV: Physical violence; SV: Sexual violence; EV: Emotional violence.
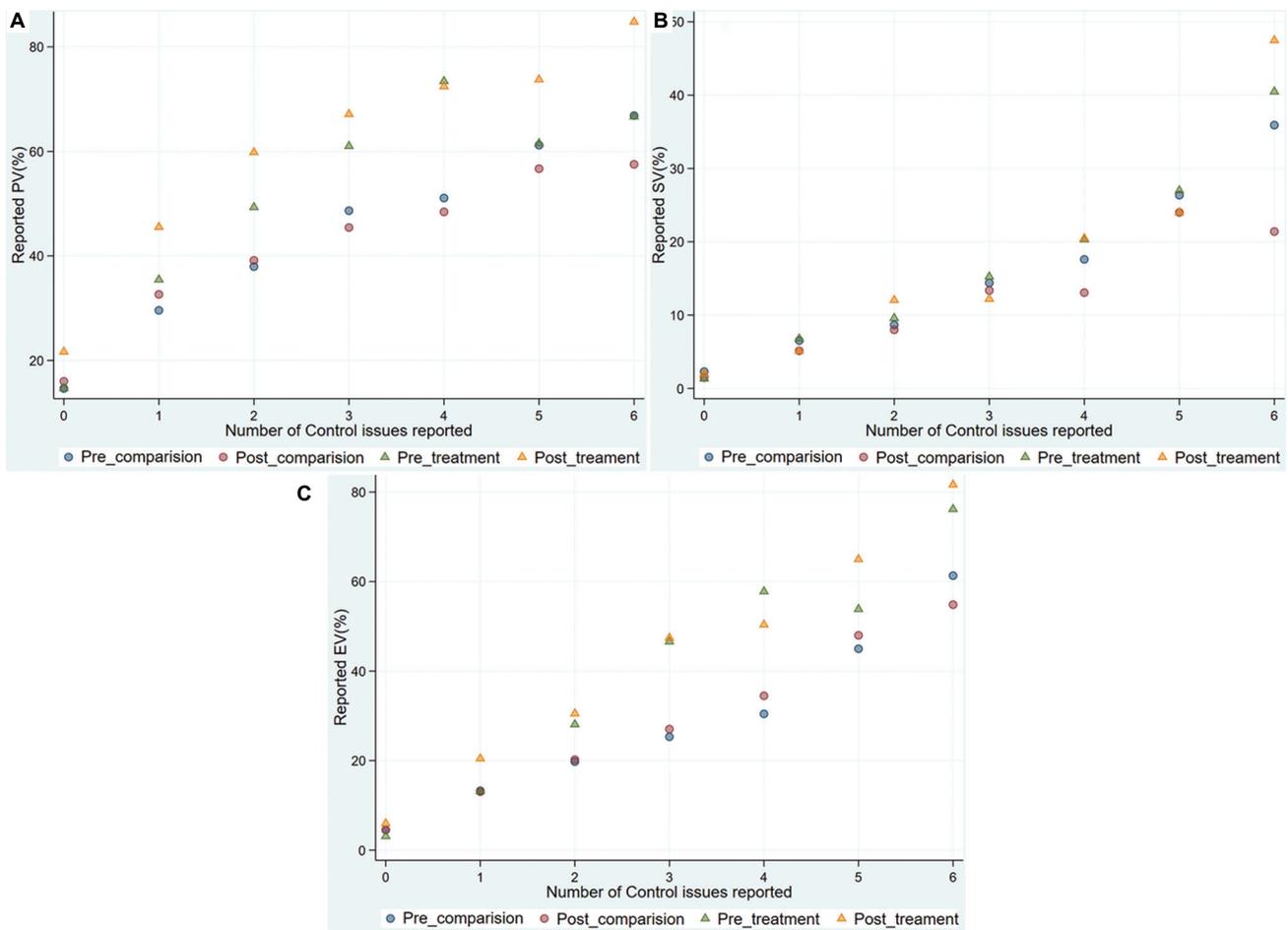
Figure 1. Number of control issues reported and incidence of IPV (%). (A) Physical violence. (B) Sexual violence. (C) Emotional violence
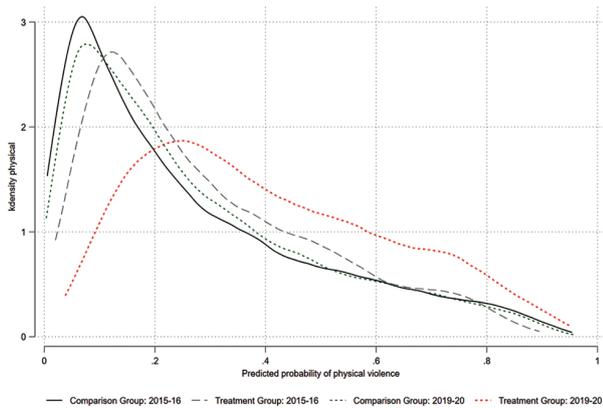Abbreviations: PV: Physical violence; SV: Sexual violence; EV: Emotional violence.

Figure 2. Predicted probabilities of PV for the treatment and comparison groups before and after exposure to the NEM drought
Abbreviations: PV: Physical violence; NEM: Northeastern monsoon.

group. The corresponding numbers are 15,744 and 2723 for the comparison and treatment groups, respectively, in 2019 – 2021.

3.2. Exploratory analysis

3.2.1. Incidence of IPV in treatment and comparison groups

The row labeled (T – C) in Table 2 shows the relative proportions of respondents reporting IPV before and after the exposure to the drought in treatment and comparison groups. The treatment group had a marginally higher proportion of respondents reporting PV than the comparison group before the exposure, significantly at the $p = 0.1$ level. However, the difference grew considerably post-exposure and became significant at the $p = 0.01$ level. Similar results were observed for SV and EV, indicating that the treatment and comparison groups diverged further for all forms of IPV after drought exposure.

3.2.2. All forms of IPV aggravated in the treatment group after drought exposure

The column labeled $(t_1 – t_0)$ in Table 2 presents the change in the proportions of respondents reporting IPV in both

Table 4. Subsample analysis

	Model with the urban sample and full controls			Model with the rural sample and full controls		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables	PV	SV	EV	PV	SV	EV
Year	1.150	0.729	0.824	1.085	0.889	1.069
Base: 2015 – 2016	(0.143)	(0.184)	(0.133)	(0.0811)	(0.105)	(0.102)
Drought: yes	1.531**	1.016	1.032	1.571***	0.387***	1.016
(Base: no)	(0.272)	(0.375)	(0.232)	(0.179)	(0.0616)	(0.126)
Year*Drought	1.447	1.980*	1.542	1.496**	1.067	1.460**
	(0.407)	(0.779)	(0.417)	(0.285)	(0.233)	(0.235)
Respondent-level controls	Y	Y	Y	Y	Y	Y
Partner level controls	Y	Y	Y	Y	Y	Y
Household-level controls	Y	Y	Y	Y	Y	Y
District fixed effects	Y	Y	Y	Y	Y	Y
Constant	1.042	0.00496***	0.0946*	0.126***	0.0210***	0.173***
	(1.448)	(0.00628)	(0.116)	(0.0973)	(0.00930)	(0.105)
Pseudo R^2	0.2984	0.3135	0.3179	0.2286	0.2153	0.2239
Observations	7,861	5,561	7,345	21,781	19,908	21,523

Note: Robust standard errors in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$.
Source: Authors' computation using unit-level data from NFHS-4 and NFHS-5.
Abbreviations: PV: Physical violence; SV: Sexual violence; EV: Emotional violence.

the treatment and comparison groups, comparing the "before" and "after" periods. Although the proportion of respondents reporting PV increased only marginally and insignificantly for the comparison group states, it increased by approximately 13% points for the treatment group (Andhra Pradesh and Karnataka). This increase was statistically significant at the $p = 0.01$ level. The proportion of respondents reporting SV decreased over time in the comparison group but increased in the treatment group. This change in SV over time was statistically significant at the $p = 0.01$ level for both groups. EV increased by about 9 percentage points for the treatment group, a change that was statistically significant at the $p = 0.01$ level, whereas it increased insignificantly in the comparison group. Thus, all forms of IPV registered a statistically significant increase in the treatment group, unlike in the comparison group.

3.2.3. Controlling behavior of partners in the treatment and comparison groups

Several studies have linked controlling behavior by intimate partners with IPV in women (Antai, 2011; Dhanaraj & Mahambare, 2021). We test our first hypothesis that there is no difference in the controlling behavior of intimate partners between states exposed to rainfall shocks (treatment group) and those not exposed (comparison group). The NFHS asks respondents about the number of "control issues" they face.

We begin by exploring how the number of reported control issues changed between 2015 – 2016 and 2019 – 2021. We calculated the point-biserial correlation between the variables "year" and "number of control issues reported" for the states exposed and not exposed to drought. As stated, "year" is a binary variable (0 for NFHS-4 (2015 – 2016) and 1 for NFHS-5 (2019 – 2021)). The variable representing the number of control issues faced ranges from 0 to 6. The point-biserial correlation between "year" and "number of control issues reported" for the comparison group (states not exposed to drought) is −0.0142; ($n = 29652$; $p < 0.05$). The negative correlation coefficient indicates that the number of control issues faced by respondents from non-drought-exposed states decreased over time. Although the correlation is statistically significant, it is not substantively significant.

For the states exposed to drought, the point-biserial correlation coefficient is 0.1382 ($n = 4938$; $p < 0.01$). The positive, substantively and statistically significant correlation coefficient indicates the respondents in drought-exposed states reported a significantly higher number of control issues from their intimate partners.

We further explored whether respondents with controlling partners reported a higher incidence of PV by calculating the point-biserial correlation between the number of control issues and the incidence of PV for the

treatment and comparison groups, both before and after exposure to the NEM drought. The results are shown in Table S3. The following observations were made:

a. The correlation coefficients between the number of control issues and the incidence of PV were significant at $p = 0.01$ level across all groups, indicating a strong association between having a controlling partner and experiencing PV.

b. The coefficient for the comparison group decreased from 0.3253 in 2015 – 2016 to 0.2797 in 2019 – 2021, suggesting that although the relationship remained strong and positive, its magnitude decreased over time.

c. Conversely, the coefficient for the treatment group increased over the same period, from 0.3727 to 0.429, implying that for respondents in states exposed to drought, the relation between having a controlling partner and experiencing PV strengthened over time.

3.2.4. Controlling behavior of partners and IPV

We estimated the association between the number of control issues a woman faces and the incidence of PV. As the direction of the relationship is uncertain, we followed Acock (2018), using the number of control issues reported as the row variable and the incidence of PV as the column variable. We conducted separate analyses for states exposed to rainfall shock, using Kruskal's gamma and Kendall's tau-b as measures of association to demonstrate concordance. We hypothesized that a woman facing numerous control issues would also report IPV, and conversely, a woman reporting IPV would likely report control issues as well. The results of these analyses are presented in Tables S4-S6.

Figure 1A-C show the percentage of women reporting each form of IPV based on the number of control issues faced. These figures are derived from the data, as shown in Tables S4-S6. Figure 1A shows a clear positive association between the number of control issues reported and the incidence of PV. Notably, respondents in non-drought-exposed states reported lower incidences of PV in 2019 – 2021 when faced with more than two control issues. In contrast, for states exposed to drought, the incidence of PV was higher across nearly every control issue category. Similarly, Figure 1C shows a strong positive association between controlling behavior and EV, although no clear pattern emerges for SV in Figure 1B.

3.3. Effect of drought on IPV: The DID estimation

Table 3 presents the results of the DID for both models: one without controls and one with a full set of controls. Both models incorporated district-level fixed effects, and standard errors are clustered at the district level.

The DID estimator reveals an increase in the odds of PV, SV, and EV in the states affected by the NEM drought across both models. These results are significant at $p = 0.01$ level for all forms of IPV, except for SV in the model with full controls.

In the model without controls, exposure to the NEM drought is associated with an approximate 83% increase in the odds of PV, whereas the effect is slightly reduced to a 48% increase when a full set of controls to applied. The corresponding increase in odds for SV is 114% in the model without controls and approximately 25% in the model with controls, although the estimates for SV are not statistically significant. For EV, the DID estimator indicates a 103% increase in odds in the model without controls and a 44% increase in the model with a full set of controls. These estimates demonstrate that exposure to the NEM drought is significantly associated with increased odds of PV and EV at the 1% significance level.

In an auxiliary regression, we calculated the predicted probabilities of PV using our DID framework. We then generated kernel density plots for four groups: the comparison group in 2015 – 2016, the treatment group in 2015 – 2016, the comparison group in 2019 – 2021, and the treatment group in 2019 – 2021. These plots are presented in Figure 2, and two key observations emerge:

a. The respondents in the treatment group, which includes the states of Andhra Pradesh and Karnataka, had marginally higher predicted probabilities of PV in the baseline (2015 – 2016). This finding aligns with the results shown in Table 2, where the difference in the proportions of respondents facing PV between the treatment and comparison groups in 2015 – 2016 was statistically significant at $p = 0.10$ level.

b. The predicted probabilities of PV increased significantly for respondents in the treatment group pre-exposure to the NEM drought. This finding further supports the results presented in Table 2, which shows that the difference in the incidence of PV between the comparison and treatment groups has grown nearly eight-fold. In addition, the statistical significance of this difference was improved to the $p = 0.01$ level.

3.3.1. Subsample analysis

To further explore the effect of the NEM drought on IPV, we conducted a subsample analysis to examine whether the impact differs between rural and urban areas. The logic behind this approach is that if the NEM drought affects IPV through reduced agricultural output and income, its effect would likely be more pronounced in rural areas. The results of this subsample analysis are shown in Table 4. In the rural areas of states affected by the NEM drought, the odds of

PV increased by 50%, with statistical significance at the 5% level. EV also saw an increase of 46% ($p < 0.05$). However, the estimates for SV in rural areas were not statistically significant. In contrast, the urban sample exhibits a 98% increase in the odds of SV, which is significant at the 10% level.

3.4. Robustness, model diagnostics, and goodness of fit

3.4.1. Robustness check

Falsification test: To ensure the internal validity of our results, we conducted two falsification tests:

a. Reversing the timeline: We reversed the "pre" and "post" periods. The estimation results were the exact opposite of the actual results and statistically significant (Table S7).

b. Switching the timeline: We also tested by limiting the "pre" period to 2015 and grouping data from 2016, 2019, and 2020 as the "post" period. Table S7 presents these results, which show that exposure to drought is no longer associated with increased odds of IPV. This further supports the internal validity of our original results, as the effect of drought exposure is no longer observed.

Both falsification tests, which involved changing the drought exposure timeline, confirm that our findings are not a result of mechanical errors and that there is a strong association between drought exposure and increased odds of IPV.

3.4.2. Model diagnostics and goodness of fit

To assess the goodness of fit of our estimated model, we applied the classification test and the receiver operating characteristic (ROC) curve. The classification test compares the model's predicted response (positive for IPV or negative) with the actual observations. A well-fitted model should correctly identify both positive and negative outcomes. Here, we discuss the results of the PV model.

Table S8 shows that the model predicted positive responses for 5607 observations, of which 3807 were correctly classified as positive ($y = 1$), whereas 1800 were incorrectly classified because the actual response was negative ($y = 0$). Of the 24,493 observations for which the model predicted a negative response, 19,909 were correctly classified, whereas 4584 were incorrectly classified. The overall classification accuracy of the PV model is 78.79%. For the SV and EV models, the correct classification rates were 94.02% and 87.97%, respectively (Tables S9 and S10).

We further calculated the area under the ROC curve, as shown in Figures S1-S3. The area under the ROC curve ranges from 0.5 to 1.0 and is used to measure the model's ability to distinguish between subjects who experience the outcome of interest and those who do not (Hosmer *et al*., 2013). The area under the ROC curve for our PV model is 0.8207, for the SV model, it is 0.8461, and for the EV model, it is 0.8281. According to Hosmer *et al*. (2013), these values indicate that the models demonstrate excellent discrimination and fit well.

For the PV model with full controls, the *pseudo R^2* value is 0.2402, indicating that the model explains approximately 24% of the variation in the data. Similarly, for the SV and EV models, the *pseudo R^2* values are 0.2274 and 0.2324, respectively, demonstrating good model fit.

4. Discussion

Recent studies have explored the complex relationship between droughts and IPV, producing varying results (Cools *et al*., 2020; Cooper *et al*., 2021; Epstein *et al*., 2020). Rai *et al*. (2021) examined this relation within the Indian context but found no statistically significant link, likely due to the overlap in the data collection period with the drought, which may have limited the ability to capture the full impact of the drought. In contrast, our study aimed to resolve this ambiguity using a dataset in which the recall period for domestic violence modules aligns with the timeframe of the NEM drought, allowing us to assess the drought's effect more comprehensively.

We began by examining whether the treatment and control groups had similar IPV incidences during 2015 – 2016. Using proportions tests (Table 2), we found that the treatment group had a marginally higher proportion of respondents experiencing IPV, except for those with SV, in 2015 – 2016. The differences increased further in 2019 – 2021, where all three forms of IPV registered a statistically significant increase for states exposed to the NEM drought. These results are consistent with Epstein *et al*. (2020) findings and contradict those of Cools *et al*. (2020) and Cooper *et al*. (2021). In the Indian context, Rai *et al*. (2021) also reported increased PV post-exposure to drought; however, their result was not statistically significant. Our dataset captured the full effects of the drought, enabling us to find statistically significant results.

The NFHS asks a question regarding the number of "control issues" the respondent faces. We explored how the number of reported control issues changed in 2015 – 2016 and 2019 – 2021 (Table S3). The negative sign of the point-biserial correlation coefficient (-0.0142; $n = 29652$; $p < 0.05$) indicates that the number of control issues reported by respondents from states with no exposure to rainfall shock has a negative relationship with the number of control issues. This suggests that the number

of control issues faced by the respondents decreased over time. However, the magnitude of this correlation is not substantively significant. Conversely, a positive and substantive, as well as statistically significant point-biserial correlation coefficient (0.1382; n = 4938; p < 0.01) for states exposed to drought indicates that respondents in these states faced a statistically higher number of control issues from their intimate partners. Our results are similar to those of Cooper *et al.* (2021), who found a positive relationship between exposure to drought and controlling behavior by partners among women from Asian and Latin American countries, even though they could not find such an association between drought and other forms of IPV. Our results also align with Epstein *et al.* (2020), who found strong associations between exposure to severe drought and the likelihood of having a controlling partner.

It is important to note that the question regarding the controlling partner does not have a recall period that is limited to the past 12 months. Thus, a woman who has ever faced any control issues with a partner will report to a controlling partner. However, exposure to drought has been shown to increase controlling behavior.

Controlling behavior by intimate partners is often linked to IPV in women (Antai, 2011; Dhanaraj & Mahambare, 2021). We further explored whether respondents with controlling partners also report a higher incidence of PV by calculating the point-biserial correlation between the number of control issues and the incidence of PV in the treatment and comparison groups separately for the period before and after exposure to the NEM drought. The results are presented in Table S3. We observed a strong association between having a controlling partner and experiencing PV. Although the size of the point-biserial correlation coefficient decreased from 2015 – 2016 and 2019 – 2021 for the comparison group, it increased for the treatment group, further strengthening the finding that drought exposure intensifies partners' controlling behavior.

Having a controlling partner is a risk factor for IPV. Figure 1A-C were generated by plotting the percentage of women reporting a particular form of IPV for each number of control issues faced. A clear positive association between the number of control issues reported and the PV reporting is evident in Figure 1A. We also observed that respondents in states not exposed to drought reported a lower incidence of PV in 2019 – 2021 for more than two control issues. In contrast, for the states exposed to drought, the incidence of PV was higher for almost every control issue category. It is possible that decreasing income due to drought led to strife between partners, and the more controlling the partner, the more likely this strife resulted in PV. We did not find any clear relationship between the number of

control issues and the incidence of SV in states exposed to drought. Conversely, a distinct decline is observed in such cases for the comparison group (Figure 1B). As shown in Figure 1C, the incidence of EV for the number of control issues provides a clearer picture: the incidence was higher for the treatment group post-exposure and lower for the comparison group. One common thread among all three types of IPV is that the more controlling the partner, the higher the incidence of IPV. The incidence of IPVs has consistently increased with the number of control issues. Dhanaraj and Mahambare (2021) found that working women who faced controlling behavior from their partners also experienced a higher incidence of IPV through the *male backlash* channel. We found a strong, positive association between the working status of women and IPV, even after accounting for the controlling behavior of their partners. The pathway through which the controlling behavior of partners increases IPV requires further research.

We found that the difference in the incidence of IPV between the states exposed to the NEM drought and those not exposed widened over time. The DID estimates in models with a complete set of control variables show that the odds of PV increase by approximately 48% among respondents exposed to the NEM drought. Similarly, the odds of EV increase by 44%. These results are significant at the 1% level of significance. Although Rai *et al.* (2021) found a positive relationship between drought and PV, their results were not statistically significant. The main reason for this may be that the data recall period during data collection did not coincide with the drought period, which may have led to an insignificant result. Our study improves upon Rai *et al.* (2021) by accurately capturing the effect of drought on IPV, which is one of the reasons for obtaining highly significant results in our study. Our findings are consistent with Epstein *et al.* (2020), who reported an increased risk of PV in women exposed to both mild and severe droughts.

We suspect that the causal link between drought and IPV is driven by increased stress following reduced income. As discussed earlier, the NEM drought adversely affected agricultural output. Decreased agricultural output translates into economic stress, which may intensify IPV. However, we cannot test this statistically, as the NFHS dataset does not contain information about income or agricultural production. This could serve as a future research agenda.

Following the logic that drought affects agricultural output, we suspected a heterogeneous effect of exposure to NEM drought between rural and urban areas. We estimated the models separately for rural and urban samples. The results are interesting: the rural areas of

states affected by the NEM drought saw a 50% increase in the odds of PV, and this result is significant at the 5% significance level. The odds of EV increased by 46% ($p < 0.05$). The urban sample showed no statistically significant increase in the odds of PV and EV post-exposure to the rainfall shock. The estimates for SV are statistically insignificant for rural areas but show a 98% increase in the odds for the urban sample, which is significant at the 10% level. One plausible explanation for the difference in the change in odds of PV and SV between rural and urban areas is that PV is more visible than SV. It is easier for SV to go unnoticed by neighbors in urban areas. Social tolerance toward wife-beating is more prevalent in rural areas; thus, PV may be the preferred method for expressing aggression. Furthermore, respondents in rural areas might be more open to sharing incidences of SV than their urban counterparts.

The heterogeneous effect of drought on rural and urban samples also supports our suspicion that the pathway between drought and IPV runs through low income. Rural areas are predominantly responsible for agricultural output; thus, a decline in this sector is likely to affect income more significantly. However, any conclusive comment can be made using a dataset that includes information about household income in addition to the domestic violence module of the NFHS. Our results also highlight the implications for policymakers. Providing better government support during droughts could help mitigate the incidence of IPV, especially in rural areas directly affected by a reduction in agricultural income. Wage employment programs, properly targeted subsidies, and similar initiatives could relieve financial stress in rural areas during periods of low rainfall, thereby keeping the IPV under control.

As mentioned earlier, exposure to stressors like drought intensifies controlling behavior in partners. Even if no visible incidence of PV, SV, or EV develops from such a stressful situation, a considerable increase in controlling behavior alone can make life difficult for women. Further studies are needed to explore whether controlling behavior and IPV are mediation. One possible policy intervention could focus on changing the mindsets of male partners since control issues are likely a manifestation of deeper societal or psychological factors.

4.1. Limitations

Our study faces the typical limitations of secondary data-based research. The responses are self-reported by victims of IPV and may suffer from recall bias and underreporting. In addition, we recognize the potential of mixed-methods research in which qualitative interviews with women could complement a scientifically drawn sample. The lack of longitudinal databases also severely limits causal inference regarding the covariates of IPV.

5. Conclusion

This study aimed to understand the impact of drought on IPV in India, thereby improving previous studies by incorporating a more comprehensive set of covariates and using data that effectively captures the effects of drought. To maintain the integrity of the results, one major drought-affected state was excluded from the analysis to avoid contamination due to the onset of COVID-19. Our findings revealed a strong association between exposure to NEM drought and an increased incidence of PV and EV. Although SV was also positively associated with drought, the relationship was not statistically significant. In addition, our analysis highlights the heterogeneous effects of drought across rural and urban areas. In rural areas, we found a statistically significant relationship between exposure to the NEM drought and both PV and EV. In urban areas, although no significant relationship emerged between PV and EV, a statistically significant association for SV.

We suspect that the link between drought and increased IPV may be mediated by a decline in agricultural incomes. However, since the NFHS does not collect income data, this hypothesis could not be directly tested. Although household assets are recorded, they tend to change slowly and are not suitable proxies for income in causal analyses. This study established a clear, strong, and positive association between drought exposure and IPV. As drought itself cannot be influenced by IPV, we contribute to the existing literature by presenting strong evidence of drought's effects on IPV in the Indian context.

Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Durgesh C. Pathak
Formal analysis: Durgesh C. Pathak
Methodology: Durgesh C. Pathak
Writing-original draft: All authors
Writing-review & editing: Durgesh C. Pathak

Ethics approval and consent to participate

The DHS and the NFHS obtained informed and voluntary consent from all survey participants. Permission to use DHS/NFHS data for this study was granted through the DHS program when downloading the datasets. As this study involves the analysis of de-identified secondary data, specific ethics approval for this analysis was not required.

Consent for publication

Not applicable.

Availability of data

The study utilized secondary data from the DHS. The dataset is publicly accessible and can be obtained by registering on the DHS platform.

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