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Air Pollution and Intimate Partner Violence in India

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Abstract

We combine individual-level data from the Demographic and Health Survey for India with high-resolution spatial data on air pollutants to investigate how exposure to high levels of PM2.5 influences spousal violence. For identification, we use atmospheric wind directions as an instrument for local pollution concentrations. We find that a 10 $\mu g/m^3$ increase in PM2.5 levels has a statistically significant impact on intimate partner violence, raising the incidence of any violence by 4.7% over the sample mean. Heterogeneity analysis shows the effects are concentrated among rural households and poor households. We also find that air pollution in rural areas is associated with lower probability of both women and men working. This is consistent with the hypothesis that air pollution could affect intimate partner violence indirectly through reduced employment.

Keywords particulate matter · intimate partner violence · India

JEL Classifications J12 · Q53

1 Introduction

Air pollution has wide-ranging effects on people's well-being. It affects people's physical health increasing cardiovascular problems and mortality (e.g., Lelieveld et al., 2015; Hoek et al., 2013; Miller et al., 2007). It also affects mental health and

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depression (Balakrishnan and Tsaneva 2023; Lin et al., 2017; Chen et al. 2024). Air pollution has also been shown to have important effects on non-health outcomes, including cognition, labor supply, worker productivity and decision-making (Aguilar-Gomez et al., 2022). A higher level of air pollution has also been associated with violence and aggressive behavior (Berman et al., 2019) and is linked to an increase in assault and violent crimes in the United States (Burkhardt et al., 2019; Jones, 2020) and the United Kingdom (Bondy et al. 2020).

In this paper, we extend the evidence on the non-health effects of air pollution by examining the extent to which exposure to elevated levels of ambient air pollution affects the incidence and intensity of intimate partner violence (IPV) in India. Almost all of India is exposed to pollution levels higher than the World Health Organization (WHO) standard (particulate matter, PM2.5 of $5\mu\, g/m^3$), and especially, regions in the Indo-Gangetic plains (which also have the highest populated density in India) (Ravishankara et al., 2020). India also has high levels of IPV with a lifetime prevalence of physical and/or sexual IPV reaching 35%.[1] Understanding the effects of air pollution on domestic violence in India is thus crucial for reducing the incidence and costs of violence against women.

Gender-related violence is a major public health issue worldwide due to its significant social and economic costs. For example, in Norway, victims have worse mental health and more doctor visits, lower employment and reduced earnings as well as greater use of disability insurance (Bhuller et al., 2024). Similarly, in Finland, women in physically abusive relationships experience large decreases in employment and earnings (Adams et al., 2024). In Taiwan, women's employment also decreases after the onset of violence while depression-related outpatient visits increase (Chang et al., 2023). Quantifying the magnitude of environmental stressors such as air pollution on IPV adds to the social costs of pollution - an effect which was previously absent from the true cost of pollution.

Exposure to pollution may affect IPV both directly and indirectly. The direct effect stems from the effect of pollution on the brain as it impairs cognition and increases impulsivity and aggression.[2] In addition, there could be an indirect effect from spending more time indoors in an attempt to avoid air pollution (Jafarov et al. 2023), which can lead to increased contact time between partners and more IPV. Another indirect effect could be due to the income stress resulting from pollution-induced household-level shocks. For example, in India, like in other places, there is evidence of diminished labor productivity associated with air pollution (Adhvaryu et al. 2022; Batheja, 2023; Merfeld, 2023). This can lead to income loss due to reduced employment. Negative income shocks have been linked to higher IPV around the world (Sekhri and Storeygard 2014; Cools et al. 2020; Abiona and Koppensteiner 2018; Bollman et al., 2026). For the case of India, Sekhri and Storeygard (2014) show that rainfall shocks have a significant effect on dowry deaths and domestic violence, which the authors

[1] Compared to 27% lifetime prevalence for the world and 33% for Southeast Asia (Source: https://vaw-data.srhr.org/data).

[2] In animal studies, pollution has been shown to lower levels of serotonin (Paz and Huitrón-Reséndiz 1996; Murphy et al., 2013), which regulates aggression and impulsivity (Coccaro et al., 2011; Siegel and Crockett2013).

attribute to a consumption smoothing mechanism. Bhalotra et al. (2021) further show that increase in the male unemployment rate in India is associated with an increase in the incidence of physical violence against women. In addition, reduced employment, especially for women, may decrease female bargaining power. For example, Panda and Agarwal (2005) show that Indian women who own property are less likely to experience domestic violence, while Menon (2020) finds that higher price of gold at the time of marriage is associated with higher rates of domestic violence (because of smaller gold dowries given to women).

This article presents new evidence on how air pollution affects the incidence and intensity of intimate partner violence in a developing country context. In our main analysis, we combine the fourth round (2015–2016) of the Indian Demographic and Health Survey, a nationally representative dataset which includes information on domestic violence and geographic location, with satellite-derived surface PM2.5 levels. We then estimate the causal effect of air pollution exposure in the six months prior to the survey on self-reported psychological, physical and sexual violence against women in India by using an instrumental variables strategy, instrumenting local air pollution with local wind direction. We find statistically significant positive effects on the incidence and intensity of IPV cases. Specifically, a 10 $\mu g/m^3$ increase in PM2.5 is associated with a 4.7% increase in the incidence of domestic violence. We also perform sensitivity analysis using data at the district-month level from complaints to the National Commission for Women (NCW). We find that air pollution is associated with a 7.9% increase in complaints related to violence against women to the NCW hotline. Furthermore, we show the robustness of the results using a composite measure of air quality, the AQI. Analysis of heterogeneous impacts suggests that the main results are driven by poor rural households, who also experience a decrease in employment probability associated with higher pollution.

While previous research has documented extensively the effect of climate change and weather-based disasters on domestic violence (Castañeda Carney et al., 2020), less is known about the effects of air pollution, especially in developing countries. Unlike other environmental stressors, air pollution may have an ambiguous effect on domestic violence if it's correlated with greater economic activity and incomes. Kuo and Putra (2021) and Hania et al. (2024) have previously shown a correlation between air pollution and domestic violence in OECD countries. Our study adds to this limited literature by using a robust empirical methodology to provide causal evidence for the effect of air pollution on IPV in India, where air pollution and domestic violence are both significantly higher and gender norms differ from those in OECD countries. Another contribution of our study is its focus on understanding the mechanisms that can explain how air pollution can impact IPV. While we are not able to determine the exact mechanism of action, we present evidence from heterogeneity analyses and analyses of labor market outcomes that is consistent with an indirect effect – pollution-related employment losses, especially for women, leading to income stress, lower female bargaining power or, possibly, increased contact time. Finally, our study adds to the literature examining more broadly the effect of air pollution on crime (Burkhardt et al., 2019; Bondy et al.2020; Jones, 2020). By studying the effect of air pollution on domestic violence, we add to our understanding of the full social costs of pollution and shed light on the gender inequality in the burden of these costs.

2 Data and Descriptive Statistics

In order to measure the effect of air pollution exposure on intimate partner violence, we leverage the Demographic and Health Survey household data set and high-resolution spatial data on air pollution levels and environmental variables. This section describes how we construct a data set that links data on intimate partner violence and environmental conditions.

2.1 Intimate Partner Violence Data

We use nationally representative cross-sectional data from the fourth round of the Demographic and Health Survey (DHS-4) for India collected in 2015–2016.[3] DHS uses a multi-stage stratified sampling design, with enumeration areas (DHS "clusters" equivalent to census villages), being the primary sampling unit. Using a two-stage stratified sampling approach, DHS-4 interviewed 699,686 women aged 15–49 from 601,509 households with a 98% response rate. Among them, 79,729 women completed the Domestic Violence module.[4] These questions ask women if they have experienced specific acts of physical (and severe physical) violence, as well as sexual, and psychological violence. Physical violence is measured by whether a woman has been pushed, or had an object thrown at her; slapped; hit (with a fist or an object); had arm twisted, or hair pulled. Severe physical violence includes being kicked or dragged; strangled or burned; or attacked with a knife, gun, or other weapon. Psychological violence is when a woman's partner threatened her with leaving home and taking away the kids; posed a threat to her; or humiliated her. Sexual violence involves a woman's partner forcing her to have sex when she did not want to or forcing her to do sexual acts she did not approve of. We leverage the domestic violence data with air pollution and weather data to estimate the effect of air pollution on intimate partner violence.

The responses to any domestic violence question could be "never", "often", "sometimes", and "yes, but not in the last 12 months". Following González and Rodríguez-Planas (2020), we define the following outcome variables: (1) an indicator of whether a woman experienced any form of IPV, such as physical, sexual, and psychological violence in the last twelve months and (2) count of any form of IPV incidents in the last twelve months. It is worth noting that women may not disclose certain violent acts due to several reasons, including self-respect, which may result in underreport-

[3] It should be noted that the most recent rounds of DHS dataset (2019–2021) are also available. We refrain from including the DHS round of 2019–2021 in our analysis due to the COVID lockdown period and its possible impact on both domestic violence and air pollution.

[4] A total of 83,397 women were selected for the domestic violence questions (only 1 woman per household) and only 4% could not complete the module because privacy could not be obtained or for other reasons.

ing in the sample. Therefore, aggregating IPV data using a measure for any form of IPV can potentially correct for any underreporting of specific violent acts.

DHS data also contain information on various individual and household characteristics including woman's age, woman's education, the number of children under 5, husband's age, husband's education, type of residence, religion, caste, and the household wealth index. We restrict the sample of eligible women interviewed in the domestic violence module to currently married women. This reduces the sample from 79,729 women to 61,995 women.[5] In addition, we drop observations with missing information on any household and individual control variables. The final analysis sample is thus 59,070 women.[6]

Importantly, DHS also collects the GPS locations of each cluster, enabling researchers to link DHS data to other geo-coded data, including air pollution levels, precipitation, temperature, and wind speed and directions, at the cluster level.[7] In order to preserve the anonymity of the villages, DHS randomly displaces the GPS coordinates of clusters up to 2 km in urban areas and up to 5 km in rural areas, and 1% of rural clusters are further displaced up to 10 km. We also observe the interview month in the DHS data and thus combine DHS data with pollution data and other environmental variables using location-specific and time-specific information.

2.2 Air Pollution Data

We measure the exposure of households to air pollution based on DHS cluster locations and survey month and year. Using the DHS cluster geo-coordinates, we obtain air pollution data (fine particulate matter, PM2.5) from NASA's Modern-Era Retrospective analysis for Research and Applications (MERRA-2) satellite reanalysis project (Global Modeling And Assimilation Office and Pawson 2015a). Air pollution data during our study period are reported as a 1-hour temporal data with a horizontal resolution of 0.5×0.625 degrees grid. Our study period for the main analysis is the six months prior to the date of interview. We use six months because victims might be more likely to report more recent episodes of domestic violence. In addition, pollution averaged over a longer time period may not accurately represent spikes in air pollution during some months. Sensitivity analyses are also performed using the past 3 and past 12 months as a study period of interest.

[5] We further perform selection checks and test whether air pollution affects women's marital status in Table 9.

[6] Importantly, the incidence of any IPV in the sample of 2,922 women with missing demographic information is not statistically significantly different than that of the final sample of 59,070 women (26.1% vs. 25.6%).

[7] 131 of the 28,526 geo-referenced clusters did not have GPS information and were not included in our sample. The missing GPS information is spread across the country, though more missing locations are situated in far remote areas of the country. More specifically, the missing GPS locations belongs to the following Indian States (the number of missing GPS locations within the State in brackets): Tamil Nadu (3); Kerala (1); Madhya Pradesh (2), Uttar Pradesh (1); Rajasthan (5); Punjab (4); Odisha (6); Nagaland (7); Mizoram (3); Meghalaya (2); Karnataka (1); Jharkhand (7); Jammu & Kashmir (12); Himachal Pradesh (4); Haryana (2); Gujarat (1) Delhi (1); Chhattisgarh (10); Assam (25); Arunachal Pradesh (23); and Andaman & Nicobar Islands (11).

In our study area, there are 950 PM2.5 grid-cells (as shown in the Appendix Figure A1). Following Provençal et al. (2017), we first construct the daily average measure of fine particulate matter ($PM_{2.5}$) from black carbon (BC), organic carbon (OC), windblown mineral dust ($DS_{2.5}$), sea salt ($SS_{2.5}$), and sulfate (SO_4) and then aggregate it to obtain the monthly means. The average six-month PM2.5 level during our study period is 45.87 $\mu g/m^3$, while the WHO annual recommended level is below 5 $\mu g/m^3$. The distribution of average PM2.5 in the past 6 months, as shown in Appendix Figure A2, suggests that there is sufficient variation in PM2.5 to study the relationship between pollution and IPV at different levels of PM2.5 and explore non-linearities in the dose-response function.

2.3 Weather Data

We obtain weather data including mean temperature, total precipitation, and wind speed and directions from MERRA-2 Surface Flux Diagnostics datasets available at spatial resolution of 0.5×0.625 degrees grid and at hourly frequency (Global Modeling And Assimilation Office and Pawson 2015b). For our instrumental variable, wind direction, we construct the number of days during the study period (the past 6 months) when the daily wind was blowing in the direction of the NE (0–90 degrees), SE (90–180 degrees), SW (180–270 degrees), and NW (270–360 degrees). We then divide the number of days the wind came from each direction in the last 6 months by the total number of days in that period. Appendix Figure A3 shows there is substantial variation in how wind direction affects average pollution levels in the country at different times of the year. For example, southeast wind days and pollution are closely correlated during winter months. Indian monsoon southwest winds during June through September are in the opposite trend to pollution levels. For most of the year, northeast winds correlate with pollution levels in the same direction (as shown in top left panel of Appendix Figure A3). Our identification strategy relies on time variation in the instrument from different interview months[8], as well as geographic variation in the direction of wind from different DHS clusters. We provide more discussion of the instrument below.

2.4 Descriptive Statistics

Tables 1 and 2 reports summary statistics for the analysis sample. Overall, 25.6% of women report having experienced some type of domestic violence, with 21.6% experiencing physical violence and 6.1% experiencing severe physical violence (as shown in Panel A of Table 1). 5% of women in the sample experienced sexual violence, while 10.2% experienced psychological violence.

The average age for women is 32.7, with 39% having no education and 7.8% having only primary education. 32% of women have ever worked, out of which 25.6% were paid workers. Close to three-quarters of females live in rural areas (as shown in Panel C of Table 1).

[8] Interviews happened throughout the year with just over half of the sample (54.7%) being interviewed between April and June (17.2% of all respondents interviewed in April, 19.7% in May, 17.8% in June).

Table 1 Individual- and household-level summary statistics (N=59,070)

Variable	Mean	SD	Min	Max
Panel A: Experience of domestic violence				
Incidence of intimate partner violence				
Physical violence	0.216	0.411	0	1
Severe physical violence	0.061	0.239	0	1
Sexual violence	0.054	0.226	0	1
Psychological violence	0.102	0.303	0	1
Any intimate partner violence	0.256	0.436	0	1
Intensity of intimate partner violence: count				
Any intimate partner violence	0.754	1.779	0	13
Panel B: Individual-level characteristics				
Woman's age	32.695	8.026	15	49
Woman's education:				
No education	0.391	0.487	0	1
Primary education	0.078	0.268	0	1
Incomplete secondary education	0.356	0.478	0	1
Secondary education	0.078	0.267	0	1
Number of children under 5 years	0.689	0.886	0	9
Ever worked	0.319	0.470	0	1
Paid work	0.256	0.436	0	1
Husband age	37.607	9.250	15	95
Husband education:				
No education	0.184	0.387	0	1
Primary education	0.149	0.356	0	1
Secondary education	0.532	0.498	0	1
Panel C: Household-level characteristics				
Rural	0.706	0.455	0	1
Religion (Hindu=1)	0.775	0.417	0	1
Social class (SC/ST=1)	0.375	0.484	0	1
Social class (OBC=1)	0.409	0.491	0	1
Household wealth index:				
Poor	0.403	0.491	0	1
Middle	0.205	0.404	0	1
Rich	0.390	0.488	0	1

[1] Physical violence includes whether a woman has been pushed, or had an object thrown at her; slapped; hit (with a fist or an object); arm twisted, or hair pulled. Severe physical violence includes being kicked or dragged; strangled or burned; or attacked with a knife, gun, or other weapon

[2] Sexual violence involves a woman's partner forcing her to have sex when she did not want to or forcing her to do sexual acts she did not approve of

[3] Intensity of intimate partner violence is constructed by calculating the number of incidents of physical violence, severe physical violence, sexual violence, and psychological violence in the past 12 months prior to the survey

Table 2 Grid-cell level summary statistics (Number of grid cells = 950)

Variable	Mean	SD	Min	Max
Panel A: Particulate matter ($\mu\, g/m^3$)				
PM2.5 last 6 months	45.868	18.380	5.057	105.835
Pollution bin:				
[5,35)	0.279	0.430	0	1
[35,45)	0.291	0.423	0	1
[45,55)	0.175	0.349	0	1
[55,65)	0.097	0.270	0	1
[65,75)	0.059	0.211	0	1
[>75]	0.098	0.278	0	1
Panel B: Proportion of winds in the last 6 months that originated from this direction:				
North	0.275	0.187	0	0.762
East	0.301	0.222	0	0.852
South	0.209	0.167	0	0.924
West	0.215	0.167	0	0.879
Panel C: Weather in the past 6 months prior to the interview				
Mean temperature (K)	296.398	5.899	260.532	303.396
Total precipitation (g/m^2s)	0.663	1.267	0	12.491
Wind speed (m/s)	4.445	0.828	2.327	6.988

Air pollution concentrations and weather variables, computed from daily averages at the cell level, using MERRA-2 data from 2014-2016. The proportion of wind direction is calculated by dividing the number of days the wind came from this direction by the total number of days in six months

Table 2 reports summary statistics for air pollution exposure and weather variables at a 6-month time scale, aggregated at grid cell level during our study period 2014–2016.[9] Our study area has 950 grid cells. The 6-month average PM2.5 level is 45.87 $\mu\, g/m^3$, the average temperature is 296.4 K (or, 23.25 degrees Celsius), the average precipitation is 0.67 g/m^2s, and the average wind speed is 4.44 m/s.[10]

3 Econometric Approach

Our goal is to estimate the effect of air pollution exposure on intimate partner violence. The primary estimating equation is:

$$y_{icgmy} = \beta_0 + \beta_1 PM_{i(c,y)} + W_{i(c,y)}\psi + X_i\xi + X_{i(h)}\lambda + \alpha_g + \eta_{i(m)} + \pi_{i(y)} + v_{icgmy} \quad (1)$$

The dependent variable, y_{icgmy} is the outcome of interest for woman i living in grid-cell c of the geographical region g. The size of grid-cell is approximately 53 Km. y_{icg} is an indicator for whether a woman who was interviewed in month m in

[9] The fourth round of DHS survey was carried out from January 2015 to December 2016. We map the pollutant exposure of the respondents six months before the survey. For example, a January 2015 respondent was mapped to the six-months average pollution from July 2014 to December 2014.

[10] The 6-month average PM2.5 level (45.87 $\mu\, g/m^3$) is greater than the averages at the 3- and 12-month time scales (43.01 $\mu\, g/m^3$ and 42.12 $\mu\, g/m^3$) respectively. Weather averages at 3, 6, and 12 months are nearly the same, except that 12-month average precipitation (1.11 g/m^2s) is slightly higher than the 3- and 6-month averages (0.63 g/m^2s and 0.67 g/m^2s).

survey year y has experienced intimate partner violence in the last year. The variable of interest is fine particulate matter represented as $PM_{i(c,y)}$ which is the 6-month average level of PM2.5 concentration in the grid-cell before the month of interview in survey year y. As a robustness check, we repeat the same analysis using various time scales for fine particulate matter PM2.5, including the average pollution level in the last 3 and last 12 months. The coefficient of interest is the β_1 parameter that links PM2.5 to types of IPV.

The term X_i and $X_{i(h)}$ includes a set of individual- and household-level characteristics that are plausibly unaffected by outdoor pollution levels. In particular, the individual-level characteristics include woman's age (and age square), woman's education (an indicator for having no education, primary education, incomplete secondary education, and complete secondary education), the number of children under 5 years. In addition, we include husband's age (and age square) and husband's education (an indicator for having no education, primary education, and secondary education). The household-level characteristics include indicators of type of residence (an indicator of rural), religion (an indicator of Hindu), caste (an indicator of scheduled castes or scheduled tribes and of other backward castes), and the household wealth index (an indicator of poor households).[11]

The term $W_{i(c,y)}$ includes a host of weather controls such as averages of precipitation, temperature, and wind speed measured at the grid-cell level. These controls address the concern that pollution and weather may be correlated. For example, PM2.5 is positively correlated with mean temperature and wind speed, while there is a negative correlation between PM2.5 and precipitation (as shown in Appendix Figure A4). We include a quadratic function of precipitation, temperature, and wind speed to capture non-linearities in the relationship between weather and pollution.[12]

Following Balietti et al. (2022) and Deryugina et al. (2019), we group grid-cells into geographical regions and include fixed effects for the geographical region of residence, α_g, to account for region-specific omitted variables (more details on the definition of the region below). We include month of interview, $\eta_{i(m)}$, and survey year, $\pi_{i(y)}$, fixed effects to remove any time trends and any seasonality effect. The identifying assumption is that after controlling for observable individual- and household-level characteristics, seasonality and flexible weather controls, exposure to pollution is uncorrelated with the error term, υ_{icgmy}. The error term captures all unobserved factors that influence the probability of a woman being exposed to intimate partner violence. The standard errors are clustered at the district level.

One threat to identification is that pollution may not be an exogenous shock to household behavior. For example, unobserved factors, such as household awareness about detrimental effects of pollution on human health and availability of resources to live away from high-polluted areas may introduce upward bias if women in these households are less subject to violence. If pollution reduces productivity and increases

[11] Online Appendix Table 1 provides robustness analysis without individual and household-level controls. The results are largely unchanged.

[12] Following Ranson (2014) and the evidence on nonlinear relationship between temperature and crime, we also estimate the main regression model with temperature bins instead of the quadratic function of temperature. The results, presented in Online Appendix Table 2, are robust to the different specification of temperature.

income stress, and income stress in turn raises the risk of domestic violence, then the OLS estimates of pollution on domestic violence will be upward biased as well. On the other hand, areas with higher pollution may also have more economic activity, which could be associated with lower domestic violence. This would then introduce a downward bias. In addition, the classical measurement error in the pollution variable will bias $\widehat{\beta_1}$ downwards as well.

To mitigate concerns about endogeneity in the OLS estimation, we conduct several robustness checks. These include using additional control variables for district and grid cell characteristics; using deviations of PM2.5 from the long-run average instead of the six-month pre-interview PM2.5 level; and controlling for PM2.5 concentrations in the six months following the interview. We also estimate an alternative specification with grid cells fixed effects, which identifies the effect of air pollution using within-grid cell time variation.

In addition, we use an instrumental variables approach that isolates variation in pollution from non-local sources. We chose wind directions, widely used in the economic literature (e.g., Balietti et al. 2022; Bondy et al. 2020; Deryugina et al., 2019; Herrnstadt et al., 2021), to explain the quasi-random variation in PM2.5. In the first stage, we explain the variation in PM2.5 by using the share of days during the study period that wind originated from one of the four quadrant wind direction (north, east, south, and west) as our main explanatory variable. Our instrumental variable, wind direction, varies by DHS cluster and month of interview.[13] To increase predictive power and account for the fact that winds may be clean or dirty depending on the location of the source of pollution and other geographic characteristics, we allow the impact of wind direction on local pollution to vary by geographical region. Specifically, this allows the same wind direction during the same time period to have different effects on pollution in different areas. The estimating equation is:

$$\begin{aligned} PM_{i(c,g)} \; = \; & \gamma_0 + \sum_g^G \gamma_1^g Share_{ic}^N + \sum_g^G \gamma_2^g Share_{ic}^E + \sum_g^G \gamma_3^g Share_{ic}^S + W_{i(c,y)}\psi \\ & + X_i\xi + X_{i(h)}\lambda + \alpha_g + \eta_{i(m)} + \pi_{i(y)} + u_{icg} \end{aligned} \tag{2}$$

$$y_{icgmy} = \beta_0 + \beta_1 \widehat{PM_{i(c,y)}} + W_{i(c,y)}\psi + X_i\xi + X_{i(h)}\lambda + \alpha_g + \eta_{i(m)} + \pi_{i(y)} + \epsilon_{icgmy} \tag{3}$$

where $Share_{ic}^{\omega}$ with $\omega \in \{N, E, S\}$, represents the respective shares of days in the past six months when the wind was blowing from North, East, and South in the direction where the woman i was living in grid-cell c of the geographical region g. $\mathrm{Share}_{\mathrm{ic}}^{\mathrm{West}}$ is the omitted category. The γ^g parameters are estimated based on the variation in all cells from geographical region g.

We follow Balietti et al. (2022) and Deryugina et al. (2019) and use the k-means clustering algorithm to construct geographical regions based on the latitude and longitude coordinates of grid-cell centroids. Similar to Balietti et al. (2022), we use 30

[13] Figure 1 in the Online Appendix plots the residuals from Eq. 1 for “Any IPV” against the four wind directions to assess whether the exclusion restriction is plausible – that is, whether wind direction appears correlated with the unobserved component of the outcome. We find no concerning patterns in these plots. We further plot the residuals for “Woman working” and “Husband working” – the two main mechanisms examined in this paper – against wind direction and similarly find no consistent patterns (Figs. 2 and 3 in the Online Appendix).

regions and as a robustness check, we repeat the analysis for 40 and 50 regions. The higher the total number of geographical regions, the more computationally burdensome the first-stage estimation becomes. For example, using 30 geographical regions results in 90 excluded instruments in the first stage (30 regions for each of the three wind directions: north, east, and south). On the other hand, when we use a smaller number of regions, we may lose potentially useful variation in wind direction.

Using 30 regions, we find that local wind direction is a strong predictor of air pollution in our data. Appendix Table A1 reports the regression results from the first stage using 30 geographical clusters. The F-statistic is 31.855. Appendix Figure A5 further presents first-stage evidence to motivate our identification strategy. [14] This illustration shows that the wind directions that statistically explain variations in pollution levels differ across regions. For example, winds originating from the north direction statistically explain the variation in PM2.5 levels in region 2, while the same winds do not explain the variation in PM2.5 levels in region 3, instead the east wind direction explains the pollution levels there.

4 Results

This section presents the simple OLS estimates. Then, we report the IV estimates using wind directions. Next, we explore the intensity of IPV and report the estimates using instrumental variables, including a control function approach in the Poisson model. Finally, we perform a battery of robustness checks.

4.1 OLS Estimates

We first present the OLS estimates in Panel A in Table 3. Each column of Table 3 represents a separate regression. The results indicate that the probability of intimate partner violence against Indian women increases by 1.6% points (6.3% over the sample mean of 25.6%) for every 10 $\mu g/m^3$ increase in PM2.5 (an increase equivalent to ½ of the standard deviation of PM2.5). For every 10 $\mu g/m^3$ increase in PM2.5, there is a 1.4, 0.5, 0.7, and 0.7% point (or 6.5, 8.2, 13.0, and 6.8%) increase in the probability of physical, severe physical, sexual, and psychological violence, respectively. The net impact of pollution exposure on reported types of IPV violence by women is positive and statistically significant at the 1% significance level for all measures except for severe physical violence where the significance is at the 5% level.

In Appendix Table A2, we show several robustness checks for our OLS specification. First, we show that the OLS results are very similar when we include additional controls for district characteristics (fraction scheduled caste/scheduled tribe, fraction of males who are literate, fraction of females who are literate, fraction of males who work, fraction of females who work, sex ratio) and grid cell characteristics (population density, proximity to national borders, proximity to protected areas, proxim-

[14] We additionally present the Olea-Pfluege F-statistic (estimated after a LIML model instead of a 2SLS model) that is more reliable in detecting weak instruments and more robust to heteroskedasticity. This F-statistic is similar to our main Wald F-statistic (29.277 vs. 31.855).

Table 3 Impact of average PM2.5 in the past six months on Incidence of Intimate Partner Violence

Dependent variable: Binary (0/1)	Any intimate partner violence	Physical violence	Severe physical violence	Sexual violence	Psycho-logical violence
	[1]	[2]	[3]	[4]	[5]
Panel A: OLS estimates					
PM2.5 ($\mu\, g/m^3$)	0.0016***	0.0014***	0.0005**	0.0007***	0.0007***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Panel B: IV estimates using wind directions					
PM2.5 ($\mu\, g/m^3$)	0.0012***	0.0010***	0.0005***	0.0008***	0.0007***
	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0002)
Geographic regions FEs	Yes	Yes	Yes	Yes	Yes
Month of interview FEs	Yes	Yes	Yes	Yes	Yes
Survey year FEs	Yes	Yes	Yes	Yes	Yes
First-stage (F-test)	31.855	31.855	31.855	31.855	31.855
Observations	59,070	59,070	59,070	59,070	59,070
Adj. R-squared	0.044	0.043	0.023	0.011	0.018

[1] Individual and household controls include woman's age (and age square), woman's education (a n indicator for having no education, primary education, incomplete secondary education, and complete secondary education), the number of children under 5-years, husband age (and age square), husband education (an indicator for having no education, primary education, and secondary education), an indicator of rural location, religion (an indicator of Hindu), social class (an indicator of scheduled castes or scheduled tribes and of other backward castes), the household wealth index (an indicator of poor and middle households)

[2] Weather controls include second-degree polynomials in precipitation, mean temperature, and wind speed

[3] Standard errors in parentheses, clustered at the district level. Number of clusters is 639

[4] ***denotes significance at the 1% level

[5] Appendix Table A1 reports the regression results from the first stage

ity to water). For example, the coefficient estimate for "any IPV" changes from a 1.59%-points increase per 10 $\mu\, g/m^3$ increase in PM2.5 to 1.62% points.

Next, we also show that the OLS results are robust to using the PM2.5 deviations from the long-run average instead of the actual PM2.5 in the 6-month period before the interview with all outcomes being statistically significantly affected by the deviations in PM2.5 levels. This measure is less subject to potential bias from long-run unobservables such as household awareness or availability of resources and provides reassurance that we are not capturing the effects of any permanent differences across regions. Similarly, we show that the OLS results are robust to controlling for PM2.5 pollution levels in the six months after the interview date. As expected, the lead effect is small and statistically insignificant, helping to once again rule out concerns that long-run unobservables are biasing our OLS estimates.

4.2 Nonlinear Effects of PM2.5 on Incidence of Intimate Partner Violence

Using the average PM2.5 levels in the past 6 months could mask any nonlinear effect on incidence of intimate partner violence. To examine the nonlinear effects of PM2.5 on the incidence of intimate partner violence, we create binary variables based on six pollution bins: (0–34 $\mu\, g/m^3$), (35–44 $\mu\, g/m^3$), (45–54 $\mu\, g/m^3$), (55–64 $\mu\, g/m^3$), (65–74 $\mu\, g/m^3$), and (above 75 $\mu\, g/m^3$). The estimating equation is given by

$$\begin{aligned} y_{icgmy} \quad = \quad & \beta_0 + \sum_{n=1}^{6} \beta_n \times 1\left[Bin_n\left(PM_{2.5}\right)\right] + W_{i(c,\,y)}\psi + X_i\xi + X_{i(h)}\lambda + \alpha_g \\ & + \eta_{i(m)} + \pi_{i(y)} + v_{icgmy} \end{aligned} \tag{4}$$

where the terms are defined same as in Eq. (3). Bin 1 (0–34 $\mu\, g/m^3$) is omitted category.

Figure 1 (and Appendix Table A3) displays the nonlinear effects of PM2.5 on incidence of any IPV. Results suggest that pollution levels between 35 and 44 $\mu\,\mathrm{g/m^3}$ have no effect on IPV but higher levels of exposure to pollution are positively and statistically significantly associated with incidence of IPV. Specifically, the effects of PM2.5 level in bin 3 and bin 4 are 0.038 and 0.052% points respectively, while bin 5 and bin 6 are 0.093 and 0.087% points, respectively. As pollution levels increase relative to the moderate level of pollution (base level of pollution), the size of the effect increases. In the next section, we present the results of IV estimates.

4.3 IV Estimates

We present IV estimates in Panel B of Table 3. Results are similar to the OLS estimates, but with a reduced effect size for some outcomes. For every 10 $\mu\, g/m^3$ increase in PM2.5, there is a 1.2% point increase in the probability of any type of

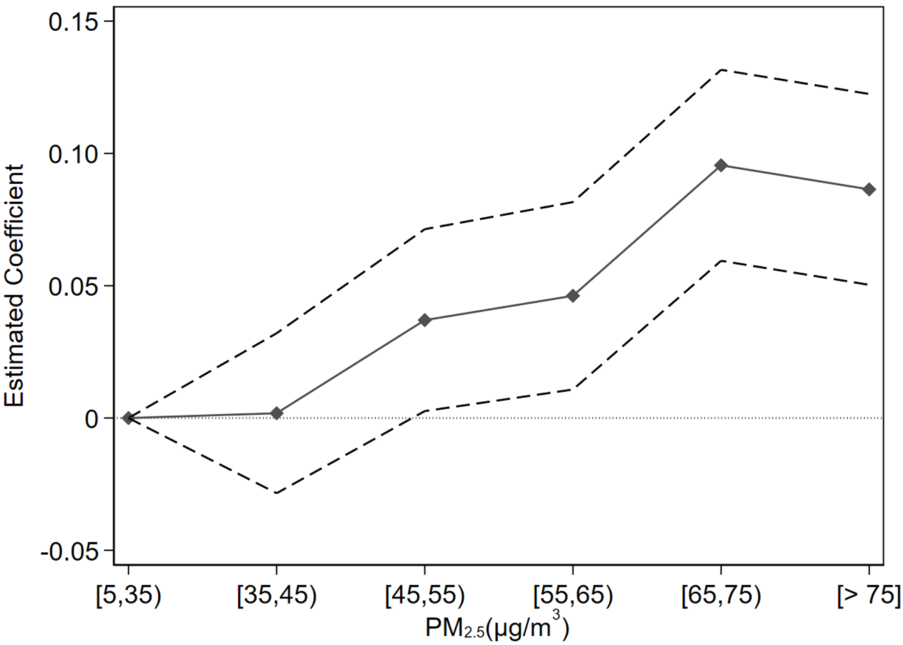

Fig. 1 Nonlinear Effects of PM2.5 on Incidence of Intimate Partner Violence. *Note*: OLS estimates are used to obtain the estimated coefficients in solid gray lines and the 95% confidence interval in dashed lines. See Appendix Table A3 for full results

IPV. Overall, our analysis indicates that pollution has statistically and economically significant effects on intimate partner violence which ranges from 0.5 to 1.2% points on average. This translates to an increase of 4.7% over the sample mean for any type of IPV, an increase of 4.6% in physical violence (and 8.2% in severe physical violence), and an increase of nearly 7% in psychological violence, and 14.8% in sexual violence. Our results are in line with the results by Sekhri and Storeygard (2014) who find that a one standard deviation fluctuation of rainfall below its long-term mean results in a 4.4% increase in domestic violence.

4.4 Impact of PM2.5 on Intensity of Intimate Partner Violence

Next, we explore the measure of intensity of intimate partner violence. To do so, we construct a count variable indicating the number of cases of intimate partner violence. About 10% of women reported experiencing one case of intimate partner violence, 5.4% reported at least two cases of violence, and between 1% and 3.5% reported cases of three to six cases of violence (as shown in the Appendix Figure A6). To estimate empirically the impact of PM2.5 on the count variable, which measures the number of violence cases, we employ a control function approach that resembles a two-stage model, similar to Braun and Villas-Boas (2023). In the first stage, the variation in PM2.5 is explained by the instruments used in this study, the wind directions in the past six months. The regression equation is the same as Eq. (1). Then, in the second stage, the count variables are regressed on the PM2.5, baseline covariates, and the residual from the first stage. The intuition is simple: the residual from the first stage regression accounts for the unmeasured confounders.

In Panel A of Table 4, the coefficients from the maximum likelihood Poisson estimates are displayed. PM2.5 concentration is positively and significantly associated with cases of intimate partner violence. Panel B of Table 4 presents the coefficients from the second stage of Poisson estimates for the control function. A 10 $\mu g/m^3$ increase in PM2.5 is associated with a 6.3% increase in the intensity of intimate partner violence.[15] Accounting for unobservables using control function approach thus reduces the magnitude of the effect from 7.5% to 6.3%, although the coefficients are not statistically significantly different from each other.[16]

4.5 Alternative source of data on domestic violence

Next, we follow Ravindran and Shah (2023) and use data from complaints made to the National Commission for Women (NCW) to test for the sensitivity of the results

[15] In all columns of Table 4, we convert the regression coefficients using the formula 100*exp (estimated coefficients) – 1 to create marginal effects.

[16] The estimated residual coefficient is positive, but not statistically significant. Appendix Figure A7 shows the scatter plot between residuals and the predicted pollution level from the first stage. It shows no clean pattern, suggesting limited correlation between the residuals and the pollution variable in the second-stage regression. In other words, there is lack of evidence of significant bias from unobservables in the count variables model.

to using an alternative source of domestic violence data.[17] Women can submit complaints to NCW via an online portal, an email, a telephone helpline, or in writing. The NCW facilitates counselling and expedited investigations. The NCW receives a variety of complaints, including cybercrime, deprivation of rights, dowry deaths, harassment at workplace. In this study, we focus on the category "Violence against women", which includes domestic violence but may also include other forms of violence. The publicly available data is available at the district-month level and the type-month level. We disaggregate the data to the district-month-type level following the approach in Ravindran and Shah (2023) - calculating the proportion of complaints of each type from the type-month level data and applying these proportions to the district-month level data. We merge the NCW's month-district-level data from 2014, 2015 and 2016 to monthly mean PM2.5 data to estimate the impact of air pollution on complaints related to violence against women.[18] It is worth noting that these complaints may be underestimating the magnitude of violence against women as women may only report more severe cases. Nevertheless, the monthly complaints of violence against women and air pollution appear to be related. For example, the cases of violence increase in the months of October, November, and December, at the same time period when air pollution is at its peak across the country (as shown in Appendix Figure A8). We present our empirical results on the impact of air pollution on violence against women in Appendix Table A4. Our models control for district, month, and year fixed effects as well as weather controls. The findings indicate that PM2.5 levels have a positive and significant association with complaints related to violence. Specifically, a 10 $\mu g/m^3$ increase in PM2.5 is associated with 0.017 more complaints to the NCW hotline. This corresponds to an increase of 7.9% given the baseline of 0.218 complaints.

4.6 Using AQI as an alternative measure of air pollution

PM2.5, or fine particulate matter, causes inflammation and oxidative stress and has wide-ranging health impacts that are well known (see e.g., Sangkham et al., 2024). As a result, PM2.5 is commonly used as a proxy indicator for air pollution. Nevertheless, we test the robustness of our results to using a measure of overall air quality, the AQI, capturing the concentration of multiple pollutants (PM2.5, PM10, and nitrogen dioxide). We follow the formula from the technical assistance document of the US Environmental Protection Agency (EPA).[19] In the online appendix, we provide specific information on how the AQI was constructed. Appendix Table A5 presents analysis using the AQI. The results are qualitatively similar to the results using PM2.5 levels.

[17] The data from NCW are available at the following URL: http://ncwapps.nic.in/frmComp_Stat_Overview.aspx.

[18] We focus on these three years to be consistent with the study period for the main sample using the DHS data.

[19] The US EPA document is available at https://www.airnow.gov/publications/air-quality-index/technical-assistance-document-for-reporting-the-daily-aqi/.

Table 4 Impact of PM2.5 on Intensity of Intimate Partner Violence

Dependent variable: Count of violence	Any IPV
Panel A: Maximum Likelihood Poisson estimates	
PM2.5 ($\mu\, g/m^3$)	0.0075***
	(0.0013)
Panel B: Maximum Likelihood Control Function Poisson estimates	
PM2.5 ($\mu\, g/m^3$)	0.0063***
	(0.0017)
First-stage residuals	0.0031
	(0.0030)
Geographic regions FEs	Yes
Month of interview FEs	Yes
Survey year FEs	Yes
Observations	59,070
Pseudo R squared	0.080
Log likelihood	-86405.606

[1] Intensity of intimate partner violence is constructed by calculating the number of incidents of physical violence, severe physical violence, sexual violence, and psychological violence in the past 12 months prior to the survey

[2] Individual and household level controls, and weather controls are included in all regressions

[3] Standard errors in parentheses, clustered at the district level

[4] ***denotes significance at the 1% level

[5] Appendix Table A1 reports the regression results from the first stage

4.7 Heterogeneity

In this subsection, we perform heterogeneity analyses splitting the sample by different characteristics. The results are summarized in Table 5. We present the heterogeneous marginal effects of air pollution on the incidence of IPV in column (1) and the intensity of IPV in column (2). Each row in Table 5 presents results from separate regressions to investigate heterogeneity.

First, we study heterogeneity by poverty status of the household.[20] We find that pollution has no effect on domestic violence among non-poor households but a strong, significant effect on poor households (0.0003 vs. 0.0023).

Next, we examine the effect of pollution by area of residence. The results show that pollution has a very small (0.0005) and statistically insignificant effect on IPV for urban households while the effect for rural households is large (0.0016) and significant. [21] Exposure to PM2.5 is roughly equal across urban and rural India. During our study period, the average PM2.5 levels in rural and urban areas were 51.04 $\mu\, g/m^3$ and 49.14 $\mu\, g/m^3$, respectively. In addition, Ravishankara et al. (2020) find that air pollution due to particulate matter has similarly negative health impacts across rural and urban India.

[20] Households are classified as poor when the wealth index reported in the DHS dataset is in the poorest and poorer category, middle when the wealth index is within the middle category, and rich when the wealth index is in the richest and richer category.

[21] In addition, we find that our effects are concentrated among poor rural households and are absent among rich rural households (effect size of 0.0025, significant at the 1% level, compared to an insignificant 0.0004).

One reason why we may see different effects of pollution on urban and rural households could be the difference in acceptability of domestic violence.[22] For example, on average, 27% of rural women reported experiencing any IPV, while in urban areas, 22% of women did. In addition, 52% of women in rural areas justified wife beating compared to 46% of women in urban areas. To further test this possibility, in Table 5, we study the effect of air pollution on domestic violence separately in a sample where women report wife beating is justified vs. a sample where they report it is not. While pollution has a bigger effect on IPV in the sample of women reporting that wife beating is justified compared to the sample of women reporting that wife beating is not justified (0.0012 vs. 0.0007), the two coefficients are not statistically significantly different from each other.

Another reason why we see different effects on IPV in urban and rural areas, however, could be that people's income and livelihoods might be affected more in rural areas if they are unable to work in the fields during high-pollution episodes. We may not see the same effect in urban areas because of less flexible labor supply. For example, Jafarov et al. (2023) study the effect of air pollution on time use in India and show reductions in time spent on outdoor labor activities for those who are self-employed and casual-laborers. Merfeld (2023) and Gupta et al. (2017) show that air pollution has negative impact on agricultural production in rural India; the effect is more pronounced in regions that cultivate labor-intensive crops like rice.

In Table 6, we test whether air pollution affects employment in our context as well. We show that air pollution is statistically significantly associated with a lower likelihood of women working - especially in agricultural employment - and a smaller decrease in the probability that husbands worked in the last 12 months (effect sizes of -0.0023 for women vs. -0.0006 for men). Importantly, the negative effects of air pollution on employment are only present in the rural sample and are small and not statistically significant for the urban sample. [23] This is consistent with the impact on IPV only found in rural areas. This is also consistent with Jafarov et al. (2023) who show lower engagement in employment-related activities during polluted days especially for residents of rural areas, and poorer households. This provides support for the hypothesis that pollution may affect IPV indirectly through reduced employment.

Lower employment may increase domestic violence because of income stress. For example, Sekhri and Storeygard (2014) show that rainfall shocks in India have a significant effect on dowry deaths and domestic violence, which the authors attribute to a consumption smoothing mechanism. Bhalotra et al. (2021) further show that increase in the male unemployment rate in India is associated with an increase in the incidence of physical violence against women.

[22] Using the DHS dataset, we coded a dummy variable for women who answer yes or don't know to questions about husband beating if: (a) the wife goes out without telling the husband; (b) wife neglects the children; (c) wife argues with husband; (d) wife refuses to have sex with husband; (e) wife does not cook food properly; (f) wife is unfaithful; and (g) wife is disrespectful.

[23] Table 6 presents results from both OLS and IV regression models and shows that the sign and magnitude of the estimates are consistent across specifications. For example, in rural areas, the effect for women working is -0.0029 under OLS compared to -0.0032 under IV. Similarly, the effect for men working is estimated as -0.0006 under OLS vs. -0.0008 under IV.

Table 5 Heterogeneous Marginal Effects: Air Pollution Effects on Intimate Partner Violence

Data	Incidence of IPV		Intensity of IPV	
	Coef./ (S.E.)	K-*P* F-stat/ [Obs.]	Coef./ (S.E.)	First-stage residuals/ [Obs.]
Overall sample	0.0012*** (0.0003)	31.855 [59,070]	0.0063*** (0.0017)	0.0031 [59,070]
Rural household sample	0.0016*** (0.0004)	27.421 [41,742]	0.0090*** (0.0018)	0.0015 [41,742]
Urban household sample	0.0005 (0.0005)	34.310 [17,328]	0.0017 (0.0028)	0.0053 [17,328]
Poor household sample	0.0023*** (0.0005)	25.223 [23,850]	0.0119*** (0.0018)	-0.0068* [23,850]
Non-poor household sample	0.0003 (0.0004)	34.529 [35,220]	0.0003 (0.0025)	0.0158*** [35,220]
Wife beating justified sample	0.0012*** (0.0004)	27.188 [29,699]	0.0055*** (0.0018)	0.0015 [29,699]
Wife beating not justified sample	0.0007* (0.0004)	36.530 [29,371]	0.0064** (0.0027)	0.0053 [29,371]
Estimates	IV		Control Function Poisson	

[1] Standard errors are in parentheses. Observations are presented in the square brackets

[2] The dependent variable in column 1 is whether the woman experienced intimate partner violence, while in column 3, the count of intimate partner violence

[3] Levels of significance: $p<0.01$*** and $p<0.05$**

Lower employment for women may also increase domestic violence because of lower female bargaining power. For example, Angelucci (2008) finds that rural women beneficiaries of the *Oportunidades* cash transfer program in Mexico report lower levels of domestic violence. Panda and Agarwal (2005) show that Indian women who own property are less likely to experience domestic violence, while Menon (2020) finds that higher price of gold at the time of marriage is associated with higher rates of domestic violence (because of smaller gold dowries given to women).

Finally, lower employment may also increase contact time which could increase IPV as well.[24] We are not able to differentiate between the different indirect effects in our data. It is important to note, however, that while Jafarov et al. (2023) show reduction in time spent working outdoors on more polluted days (an average of 7 min), they also find that the share of male members' time on activities related to unpaid care performed outdoors increases. Thus, less time spent working outdoors may not necessarily translate to more contact time indoors.

While we cannot test the direct effect of pollution on IPV through neuroinflammation and the resulting aggression, our finding that urban and rich households are not affected by pollution would be inconsistent with a direct biological effect. It is possible that urban and rich households are better able to avoid pollution (e.g., by staying at home and using air filters). Yet, previous research has found equally negative effects on health in both rural and urban areas, which makes the presence of a

[24] We additionally test the sensitivity of the results to indoor air pollution by controlling by source of fuel for cooking. The results, presented in Online Appendix Table 3, show that the results are not explained by indoor air pollution.

biological effect of pollution on IPV unlikely. Moreover, Jafarov et al. (2023) don't find a strong effect of air pollution on time use among urban households so there is little evidence for avoidance behavior among urban households. In addition, any pollution avoidance behavior like staying home may increase the contact time between spouses and thus may increase domestic violence in urban areas, which is not consistent with our findings.

Instead, our study provides suggestive evidence that the key mechanism through which pollution affects IPV is the indirect effect of pollution. This indirect effect is likely due to pollution-induced employment declines in rural areas leading to income stress, lower female bargaining power, or, possibly, increased contact time.

4.8 Robustness Checks

Our main results are robust to a number of robustness checks. First, we perform checks on sample selection given that in the main specification, the sample size is restricted to currently married women. Specifically, in columns 1 and 2 of Appendix table A6 we examine the full sample of women who answered the domestic violence module in the survey and test whether air pollution affects the probability of a woman being currently married (column 1) and the probability of a woman never having married (column 2). In column 3 we show results for all ever married women who answered the domestic violence module in the survey and examine the effect of air pollution on the probability that a woman was divorced or widowed. The null effect of pollution on marital status suggests that sample selection bias resulting from endogenous changes in marital status is not a big concern in our study. [25] We report these regression results in Appendix Table A6.[26]

In the second robustness check, we repeat our main analysis for a different number of geographical regions. As previously mentioned, the higher the total number of geographical regions, the more restrictive the first-stage regression becomes. Similar to Balietti et al. (2022), we find that the regression analysis is the same as our main results for 40 geographic regions, but the statistical significance at conventional levels does not hold when using 50 geographic regions (results shown in Appendix Figure A9).

We also repeat our main analysis for different time scales of pollution, using averages of three- and twelve-month levels of PM2.5. Overall, the findings are qualitatively the same as those in Table 3 (as shown in Appendix Table A7).

Finally, in Appendix Table A8, we use an alternative econometric specification – fixed effects by grid cells – to show that our results don't hinge on the choice of instrument. We take advantage of the fact that grid cells (roughly 55 km by 60-70 km) may contain DHS clusters (or villages) which were interviewed in different months. So we estimate our OLS regression model with grid cell fixed effects identifying the

[25] Additionally, as a robustness check, we estimate the main regression model excluding the sample of women with recent marriages (i.e., interviewed within a year of the start of cohabitation), and we find the effects are robust to this exclusion restriction (effect size of 0.0010, significant at 1% level).

[26] Two other sources of sample selection that may potentially affect the results are mortality and migration. In both cases, however, we would expect that any effect, if present, would cause a downward bias of our estimates as the people most affected by pollution or IPV die or migrate.

Table 6 Possible Mechanisms

Dependent variable: Binary (0/1)	Woman currently works		Woman works in agricultural sector		Husband currently works	
	OLS estimates	IV estimates	OLS estimates	IV estimates	OLS estimates	IV estimates
Panel A: All residences (both rural and urban)						
PM2.5 ($\mu\, g/m^3$)	-0.0022***	-0.0023***	-0.0021***	-0.0025***	-0.0005***	-0.0006***
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0001)	(0.0002)
Mean of dependent var.	0.319	0.319	0.170	0.170	0.949	0.949
Observations	59,070	59,070	59,070	59,070	59,070	59,070
F-stat		31.855		31.855		31.855
Panel B: Only rural residence						
PM2.5 ($\mu\, g/m^3$)	-0.0029***	-0.0032***	-0.0028***	-0.0034***	-0.0006***	-0.0008***
	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0001)	(0.0002)
Mean of dependent var.	0.352	0.352	0.225	0.225	0.953	0.953
Observations	41,742	41,742	41,742	41,742	41,742	41,742
F-stat		27.421		27.421		27.421
Panel C: Only urban residence						
PM2.5 ($\mu\, g/m^3$)	-0.0004	-0.0001	0.0001	0.0001	-0.0002	-0.00001
	(0.0005)	(0.0005)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Mean of dependent var.	0.239	0.239	0.039	0.039	0.940	0.940
Observations	17,328	17,328	17,328	17,328	17,328	17,328
F-stat		34.310		34.310		34.310

All regressions control for geographic region fixed effects, month of interview fixed effects, and year of survey fixed effects, individual and household level characteristics, and weather controls. Standard errors are clustered at the district level. ***denotes significance at the 1% level

effect of air pollution based on month-to-month variation within the grid. We find that the results are similar in size and statistically significant at the 5% level for the "any IPV" outcome: 1.55%-point increase per 10 $\mu\, g/m^3$ increase in PM2.5 levels, compared to 1.59% points in the main OLS model and 1.2% points in the main IV model for every 10 $\mu\, g/m^3$ increase in PM2.5. While they are also similar in size for emotional and sexual violence, the estimates are less precisely estimated, likely due to the small variation in interview months and domestic violence within the grid cell.

5 Conclusion

This paper examines the effect of particulate matter pollution on domestic violence in India. Using local wind direction as an instrument for air pollution, we find that an increase of 10 $\mu\, g/m^3$ in PM2.5 (an increase equivalent to ½ of the standard deviation of PM2.5) is associated with a 4.7% increase in the probability of women reporting recent episodes of domestic violence. We find that the effects are only present among rural but not urban households. We also find that pollution has negative effects on labor market outcomes of both women and men in rural but not urban areas. Although we cannot establish the precise mechanism linking air pollution to intimate partner violence, our results are more consistent with an indirect pathway of reduced employment than with a direct biological effect of neuroinflammation and increased aggression.

A key limitation of this study is the aggregation of the domestic violence data, which prevents us from capturing the immediate effects of pollution or examining how quickly these effects dissipate over time. Nevertheless, we take the important first step of quantifying pollution externalities in a developing country context, where the baseline pollution concentrations are several times larger than those of developed countries and resources to mitigate them are limited.

6 Appendix A: Additional Tables and Figures

Table A1 First-stage regression results

	(1)
	PM2.5
Share of the wind from the North, region 1	-37.40***
	(-3.86)
Share of the wind from the North, region 2	110.10
	(1.72)
Share of the wind from the North, region 3	46.27
	(0.91)
Share of the wind from the North, region 4	-107.40***
	(-3.36)
Share of the wind from the North, region 5	-62.94**
	(-7.57)
Share of the wind from the North, region 6	-21.49*
	(-2.02)
Share of the wind from the North, region 7	-16.43
	(-1.09)
Share of the wind from the North, region 8	11.39
	(0.46)
Share of the wind from the North, region 9	-1.43
	(-0.14)
Share of the wind from the North, region 10	-4.59
	(-0.72)
Share of the wind from the North, region 11	-12.93**
	(-2.31)
Share of the wind from the North, region 12	-17.96**
	(-3.13)
Share of the wind from the North, region 13	-7.81
	(-0.91)
Share of the wind from the North, region 14	-31.37***
	(-3.42)
Share of the wind from the North, region 15	-27.76***
	(-4.69)
Share of the wind from the North, region 16	-18.94**

Table A1 (continued)

	(1)
	PM2.5
	(-2.71)
Share of the wind from the North, region 17	10.18
	(0.82)
Share of the wind from the North, region 18	15.64
	(0.88)
Share of the wind from the North, region 19	-50.99***
	(-3.97)
Share of the wind from the North, region 20	-48.91***
	(-3.70)
Share of the wind from the North, region 21	-10.13
	(-1.07)
Share of the wind from the North, region 22	-9.28*
	(-2.20)
Share of the wind from the North, region 23	-76.90***
	(-4.71)
Share of the wind from the North, region 24	-18.27*
	(-2.24)
Share of the wind from the North, region 25	-18.82
	(-1.66)
Share of the wind from the North, region 26	-46.49***
	(-6.21)
Share of the wind from the North, region 27	-37.41*
	(-2.51)
Share of the wind from the North, region 28	-61.74***
	(-4.32)
Share of the wind from the North, region 29	-69.43***
	(-5.19)
Share of the wind from the North, region 30	-35.59**
	(-3.27)
Share of the wind from the East, region 1	6.94
	(0.73)
Share of the wind from the East, region 2	136.30*
	(2.49)
Share of the wind from the East, region 3	81.18**
	(3.10)
Share of the wind from the East, region 4	-55.25*
	(-2.18)
Share of the wind from the East, region 5	-6.04
	(-0.66)
Share of the wind from the East, region 6	-4.34
	(-0.62)
Share of the wind from the East, region 7	31.70***
	(3.38)
Share of the wind from the East, region 8	124.40***
	(7.54)
Share of the wind from the East, region 9	34.59***

Table A1 (continued)

	(1)
	PM2.5
	(4.14)
Share of the wind from the East, region 10	7.20
	(1.00)
Share of the wind from the East, region 11	9.35
	(1.71)
Share of the wind from the East, region 12	6.88
	(0.89)
Share of the wind from the East, region 13	-16.13
	(-1.59)
Share of the wind from the East, region 14	-62.19**
	(-4.22)
Share of the wind from the East, region 15	-3.92
	(-1.36)
Share of the wind from the East, region 16	38.94***
	(6.79)
Share of the wind from the East, region 17	19.28*
	(2.43)
Share of the wind from the East, region 18	32.13
	(1.94)
Share of the wind from the East, region 19	-18.23*
	(-2.07)
Share of the wind from the East, region 20	21.55*
	(2.03)
Share of the wind from the East, region 21	104.00***
	(3.57)
Share of the wind from the East, region 22	31.56***
	(8.77)
Share of the wind from the East, region 23	55.49***
	(7.90)
Share of the wind from the East, region 24	49.90***
	(7.36)
Share of the wind from the East, region 25	46.50***
	(4.52)
Share of the wind from the East, region 26	16.77
	(1.90)
Share of the wind from the East, region 27	-3.69
	(-0.28)
Share of the wind from the East, region 28	26.86*
	(2.13)
Share of the wind from the East, region 29	-2.72
	(-0.24)
Share of the wind from the East, region 30	41.31***
	(3.73)
Share of the wind from the South, region 1	1.83
	(0.15)
Share of the wind from the South, region 2	115.10*

Table A1 (continued)

	(1)
	PM2.5
	(2.01)
Share of the wind from the South, region 3	99.42***
	(4.88)
Share of the wind from the South, region 4	-96.71***
	(-3.89)
Share of the wind from the South, region 5	-6.32
	(-0.51)
Share of the wind from the South, region 6	37.75**
	(2.64)
Share of the wind from the South, region 7	-17.49
	(-1.58)
Share of the wind from the South, region 8	96.17***
	(4.85)
Share of the wind from the South, region 9	21.53*
	(2.12)
Share of the wind from the South, region 10	29.80***
	(3.98)
Share of the wind from the South, region 11	12.17
	(1.62)
Share of the wind from the South, region 12	43.81***
	(6.43)
Share of the wind from the South, region 13	27.30
	(1.19)
Share of the wind from the South, region 14	30.67***
	(4.32)
Share of the wind from the South, region 15	35.22***
	(9.67)
Share of the wind from the South, region 16	3.43
	(0.58)
Share of the wind from the South, region 17	34.26**
	(2.60)
Share of the wind from the South, region 18	28.31
	(1.51)
Share of the wind from the South, region 19	29.35*
	(2.48)
Share of the wind from the South, region 20	38.77*
	(2.55)
Share of the wind from the South, region 21	31.60***
	(3.52)
Share of the wind from the South, region 22	11.71**
	(2.70)
Share of the wind from the South, region 23	1.72
	(0.20)
Share of the wind from the South, region 24	23.51*
	(2.31)
Share of the wind from the South, region 25	11.36

Table A1 (continued)

	(1)
	PM2.5
	(0.77)
Share of the wind from the South, region 26	17.93
	(1.44)
Share of the wind from the South, region 27	-0.50
	(-0.04)
Share of the wind from the South, region 28	20.60
	(1.02)
Share of the wind from the South, region 29	0.84
	(0.04)
Share of the wind from the South, region 30	19.64
	(1.95)
Individual-level characteristics	
Woman's current age	0.06
	(1.24)
Woman's age square	-0.001
	(-1.73)
Woman's education:	
No education	0.61*
	(2.38)
Primary education	0.29
	(1.27)
Incomplete secondary education	0.33
	(1.78)
Secondary education	0.26
	(1.38)
Number of children under 5	-0.03
	(-0.60)
Husband's education:	
No education	0.20
	(0.93)
Primary education	0.20
	(1.01)
Secondary education	-0.03
	(-0.19)
Husband age	-0.04
	(-1.00)
Husband age square	0.00
	(1.16)
Household-level characteristics	
Rural	0.12
	(0.49)
Religion (Hindu = 1)	-1.18*
	(-2.63)
Social class (SC/ST = 1)	0.76*
	(2.63)
Social class (OBC = 1)	1.12***

Table A1 (continued)

	(1)
	PM2.5
	(4.19)
Household wealth index:	
Poor	-0.42
	(-1.56)
Middle	-0.34*
	(-2.10)
Mean temperature	18.71***
	(4.08)
Mean temperature square	-0.03***
	(-3.72)
Total precipitation	-1.35
	(-1.11)
Total precipitation square	0.31*
	(2.50)
Wind speed	39.35***
	(7.66)
Wind speed square	-4.53***
	(-8.08)
Geographical regions FEs	Yes
Month of interview FEs	Yes
Survey year FEs	Yes
Observations	59,070
Adj. R-squared	0.043

Notes: t statistics in parentheses. Level of significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table A2 Robustness checks

	Any intimate partner violence	Psychological violence	Sexual violence	Physical violence	Severe physical violence
Panel A: Original OLS Estimates					
PM2.5	0.00159**	0.00075**	0.00074**	0.00138**	0.00051**
	(0.00027)	(0.00015)	(0.00013)	(0.00025)	(0.00012)
Observations	59,070	59,070	59,070	59,070	59,070
Panel B: OLS with additional district-level controls					
PM2.5	0.00162**	0.00064**	0.00050**	0.00147**	0.00046**
	(0.00032)	(0.00017)	(0.00014)	(0.00028)	(0.00013)
Observations	59,060	59,060	59,060	59,060	59,060
Panel C: OLS results with 6mo deviations from 12mo long-run average					
PM2.5	0.00180**	0.00105**	0.00085**	0.00133**	0.00049**
	(0.00046)	(0.00024)	(0.00024)	(0.00043)	(0.00019)
Observations	58,986	58,986	58,986	58,986	58,986
Panel D: OLS with additional control variable for future PM2.5					
PM2.5 6mo	0.00148**	0.00077**	0.00065**	0.00120**	0.00043**
	(0.00029)	(0.00015)	(0.00014)	(0.00027)	(0.00012)
6-mo Lead Variable	0.00039	-0.00008	0.00028	0.00063	0.00025
	(0.00042)	(0.00021)	(0.00017)	(0.00040)	(0.00016)
Observations	59,070	59,070	59,070	59,070	59.070

OLS estimates are reported. All regression models include individual and household level controls, as well as weather controls. Standard errors in parentheses, clustered at the district level. *$p < 0.10$, **$p < 0.05$

Table A3 Non-linear effects of PM2.5 on the incidence of IPV

	Any IPV violence
Pollution bin: [5,35) is used as reference	
[35,45)	0.0015
	(0.0154)
[45,55)	0.0380**
	(0.0175)
[55,65)	0.0517***
	(0.0181)
[65,75)	0.0934***
	(0.0188)
[>75]	0.0868***
	(0.01847
Geographical regions FEs	Yes
Month of interview FEs	Yes
Survey year FEs	Yes
Observations	59,070
Adj. R-squared	0.069

OLS estimates are reported. Regression includes individual and household level controls, as well as weather controls. Standard errors in parentheses, clustered at the district level. *$p < 0.10$, **$p < 0.05$

Table A4 Impact of PM2.5 on Violence Against Women using NCW complaints data

	Violence Against Women
Panel A: OLS estimates	
PM2.5 ($\mu\, g/m^3$)	0.00097^{***}
	(0.00020)
Panel B: IV estimates using wind directions	
PM2.5 ($\mu\, g/m^3$)	0.00167^{***}
	(0.00036)
District FEs	Yes
Month-Year FEs	Yes
First-stage (F-test)	22.665
Observations	15,156
Adj. R-squared	0.552

[1] The dependent variable is the monthly share of complaints in each category obtained from the Complaint & Investigation Cell of the National Commission for Women across Indian districts for the years 2014, 2015, and 2016

[2] Weather controls include second-degree polynomials in precipitation, mean temperature, and wind speed

[3] Standard errors in parentheses, clustered at the district level. Number of clusters is 459

[4] ***denotes significance at the 1% level

Table A5 Effect of Air Quality Index on IPV

Dependent variable: Binary (0/1)	Any intimate partner violence	Physical violence	Severe physical violence	Sexual violence	Psycho-logical violence
	[1]	[2]	[3]	[4]	[5]
Panel A: OLS estimates					
Air Quality Index	0.0002^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}
	(0.0001)	(0.0001)	(0.00002)	(0.00002)	(0.00003)
Panel B: IV estimates using wind directions					
Air Quality Index	0.0002^{***}	0.0002^{***}	0.0001^{***}	0.0002^{***}	0.0001^{***}
	(0.0001)	(0.0001)	(0.00004)	(0.00004)	(0.00005)
Individual- and household-level characteristics	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes
Geographic regions FEs	Yes	Yes	Yes	Yes	Yes
Month of interview FEs	Yes	Yes	Yes	Yes	Yes
Survey year FEs	Yes	Yes	Yes	Yes	Yes
First-stage (F-test)	16.632	16.632	16.632	16.632	16.632
Observations	59,070	59,070	59,070	59,070	59,070
Adj. R-squared	0.043	0.043	0.022	0.010	0.017

Standard errors in parentheses, clustered at the district level. The Air Quality Index was derived from three pollutants PM2.5, PM10, and NO2 using a specific formula from the US EPA. Weather controls include second-degree polynomials in precipitation, mean temperature, and wind speed

*** denotes significance at the 1% level

Table A6 Sample selection checks

Dependent variable: Binary (0/1)	Sample selection		
	Currently married	Never married	Divorced /widowed
	[1]	[2]	[3]
PM2.5 ($\mu g/m^3$)	0.0001	-0.0002	0.0002*
	(0.0002)	(0.0001)	(0.0001)
Geographical regions FEs	Yes	Yes	Yes
Month of interview FEs	Yes	Yes	Yes
Survey year FEs	Yes	Yes	Yes
Observations	75,360	75,360	62,585
F-stat	31.296	31.296	32.271

The Table presents the results of women who answered the domestic violence module in the survey. Columns [1] and [2] show results for all women with non-missing covariates who respond to the domestic violence survey module. Column [3] shows results for ever married women. All regressions control for geographic region fixed effects, month of interview fixed effects, and year of survey fixed effects, individual and household level characteristics, and weather controls. Standard errors are clustered at the district level. Levels of significance: p<0.10*

Table A7 Impact of average PM2.5 in the past three and twelve months on Incidence of Intimate Partner Violence: IV estimates

Dependent variable: Binary (0/1)	Any intimate partner violence	Physical violence	Severe physical violence	Sexual violence	Psycho-logical violence
	[1]	[2]	[3]	[4]	[5]
Panel A: PM2.5 last 3 months					
PM2.5 ($\mu g/m^3$)	0.0008*	0.0007*	0.0002	0.0006***	0.0001
	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0002)
F-stat	15.573	15.573	15.573	15.573	15.573
Panel B: PM2.5 last 12 months					
PM2.5 ($\mu g/m^3$)	0.0011*	0.0010**	0.0005**	0.0011***	0.0009***
	(0.0006)	(0.0005)	(0.0002)	(0.0002)	(0.0003)
F-stat	32.103	32.103	32.103	32.103	32.103
Geographic regions FEs	Yes	Yes	Yes	Yes	Yes
Month of interview FEs	Yes	Yes	Yes	Yes	Yes
Survey year FEs	Yes	Yes	Yes	Yes	Yes
Observations	59,070	59,070	59,070	59,070	59,070

[1] All regressions include individual and household controls, as well as weather controls

[2] Standard errors in parentheses, clustered at the district level. Number of clusters is 639

[3] Level of significance: * p<0.10, ** p<0.05, *** p<0.01

Table A8 Geographic cell fixed effects

	Any intimate partner violence	Psychological violence	Sexual violence	Physical violence	Severe physical violence
Panel A: Original OLS estimates					
PM2.5	0.00159**	0.00075**	0.00074**	0.00138**	0.00051**
	(0.00027)	(0.00015)	(0.00013)	(0.00025)	(0.00012)
Observations	59,070	59,070	59,070	59,070	59,070
Panel B: OLS results with geographic cell FE and year of interview FE (no month FE)					
PM2.5	0.00155**	0.00051	0.00053	0.00055	0.00002
	(0.00067)	(0.00043)	(0.00038)	(0.00064)	(0.00031)
Observations	59,070	59,070	59,070	59,070	59,070

[1] All regressions include individual and household controls, as well as weather controls

[2] Standard errors in parentheses, clustered at the district level. Number of clusters is 639

[3] Level of significance: * p<0.10, ** p<0.05, *** p<0.01

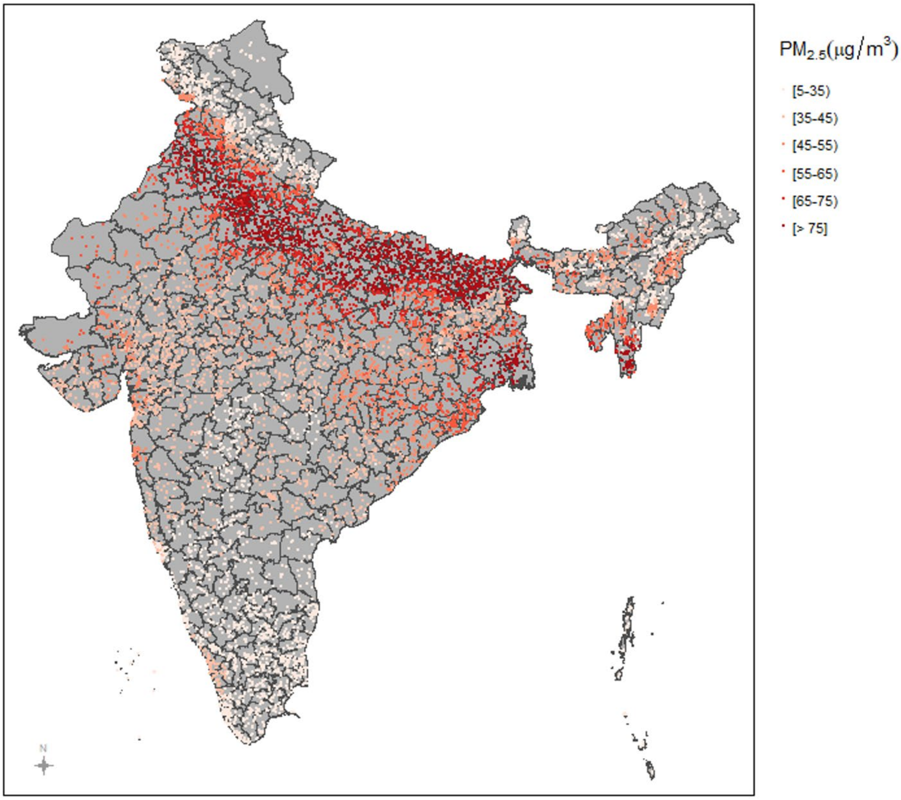

Fig. A1 Map of the Study Area. *Note:* The dots represent the average PM2.5 levels (in $\mu g/m^3$) for the past 6 months from the survey period for DHS clusters. The district boundaries are shown in gray

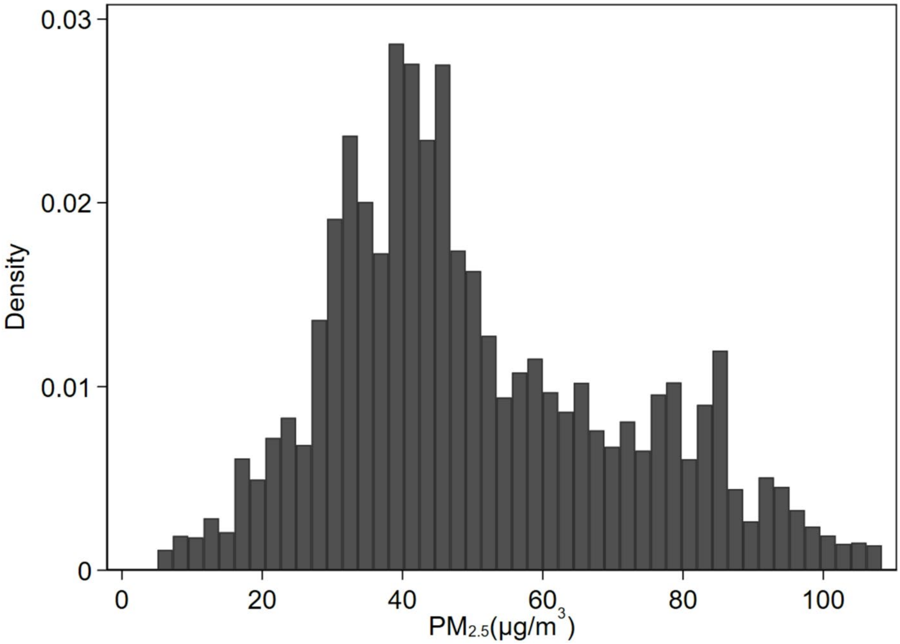

Fig. A2 Distribution of PM2.5 concentration levels

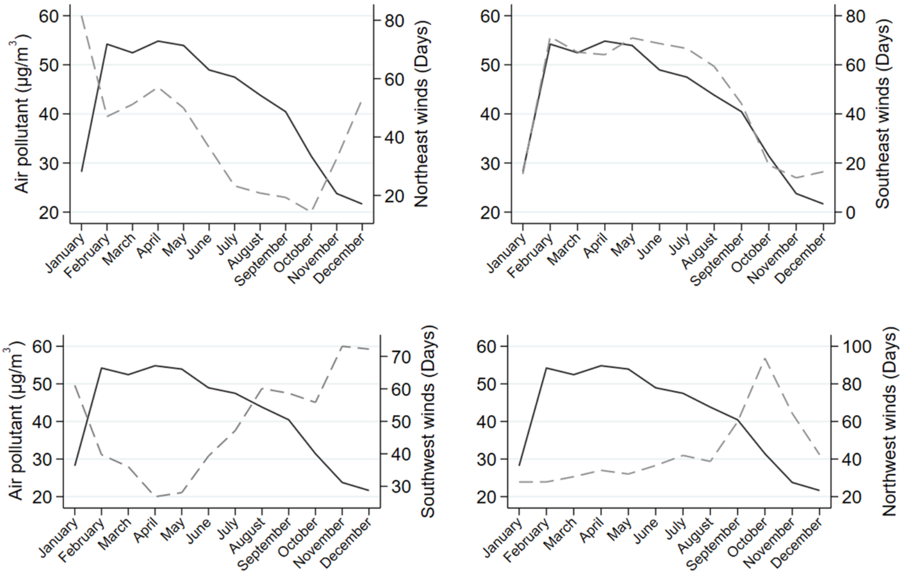

Fig. A3 Time Trend of PM2.5 and Wind days. *Note*: The figure displays the average PM2.5 levels and the number of wind days in the past 6 months before the survey. Solid gray lines represent the level of pollution, while dashed lines represent the number of wind days originating from four quadrant directions

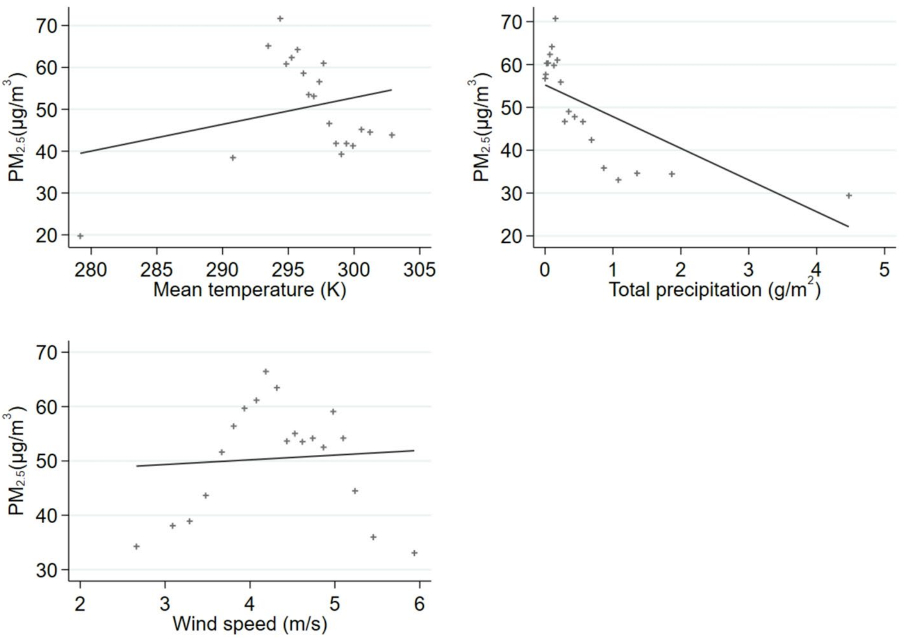

Fig. A4 PM2.5 and Weather Bin Scatterplot

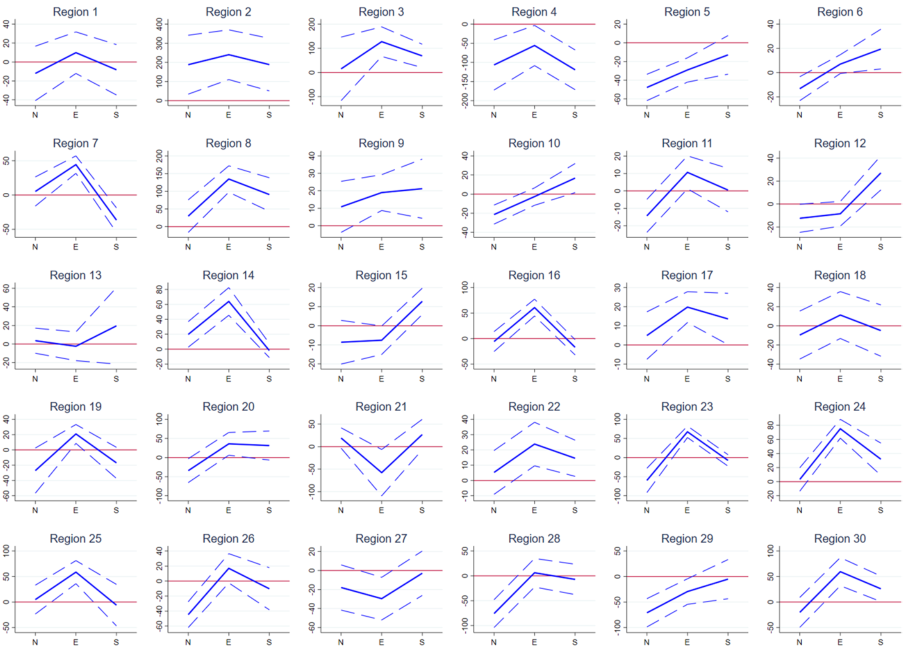

Fig. A5 Semi-annual wind direction and PM2.5: first stage estimates by regions. *Note*: The figure is obtained by regressing PM2.5 on the interaction term between the share of wind directions and geographic clusters, controlling for geographic regions, interview month, and year of interview FEs. Standard errors are clustered at the district level. The coefficients are represented by a solid blue line, while the 95% confidence interval is represented by a dashed line

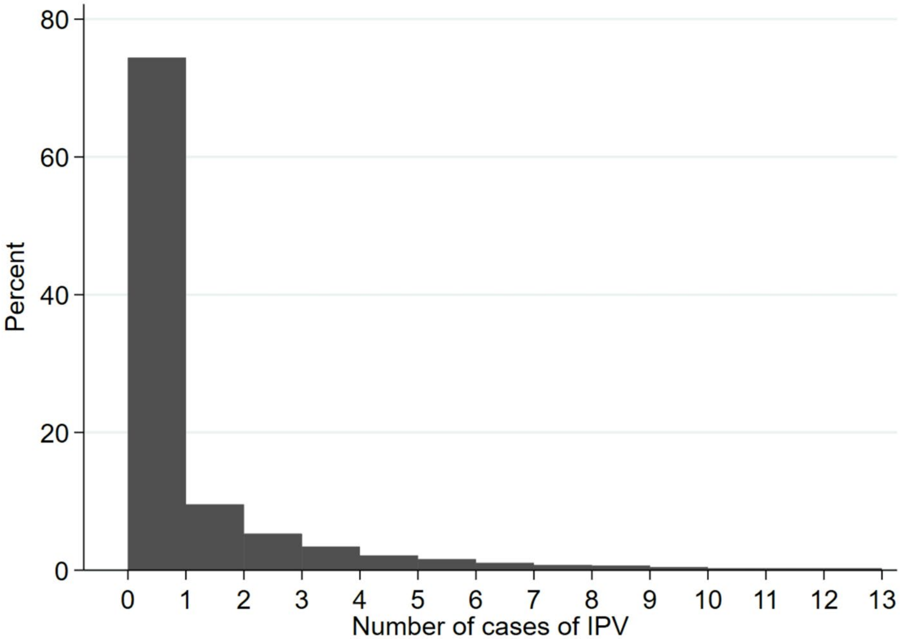

Fig. A6 Distribution of cases of intimate partner violence

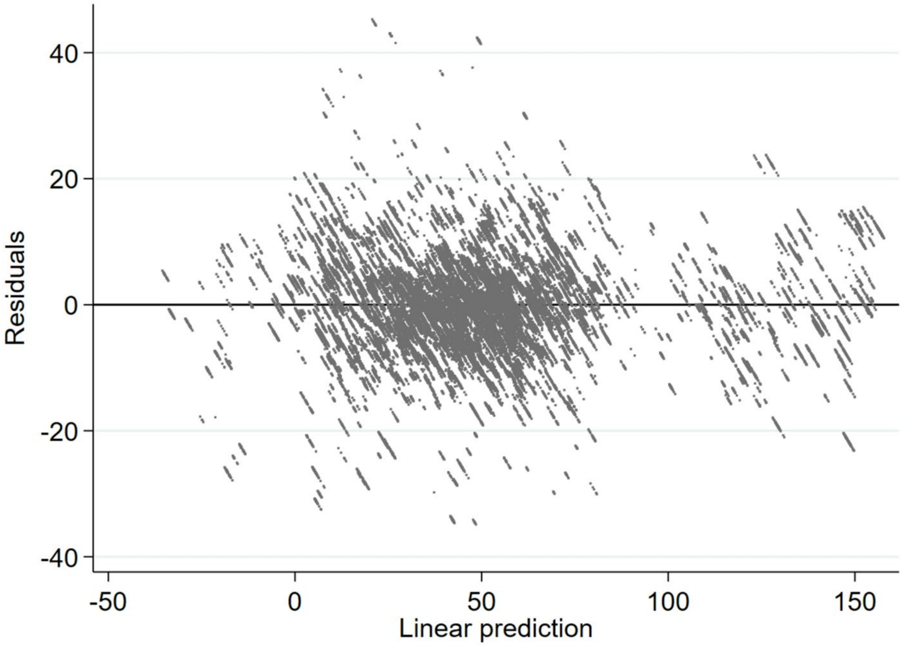

Fig. A7 Scatter plot of residuals from the first stage of the control function approach

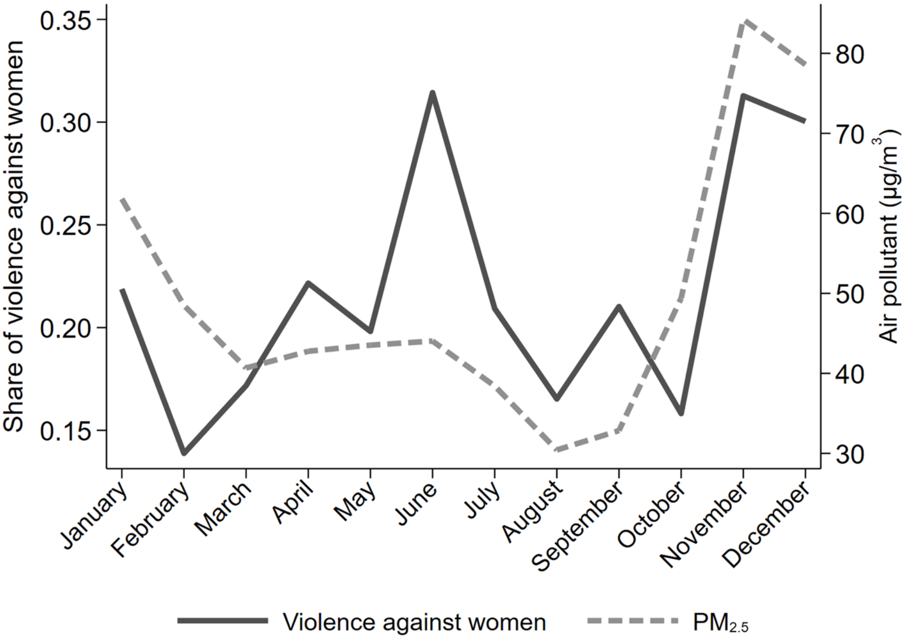

Fig. A8 Trends of violence against women using NCW complaints data and air pollution. *Note*: The violence against women is reported as a monthly mean value across Indian districts (459 districts) for the years 2014, 2015, and 2016

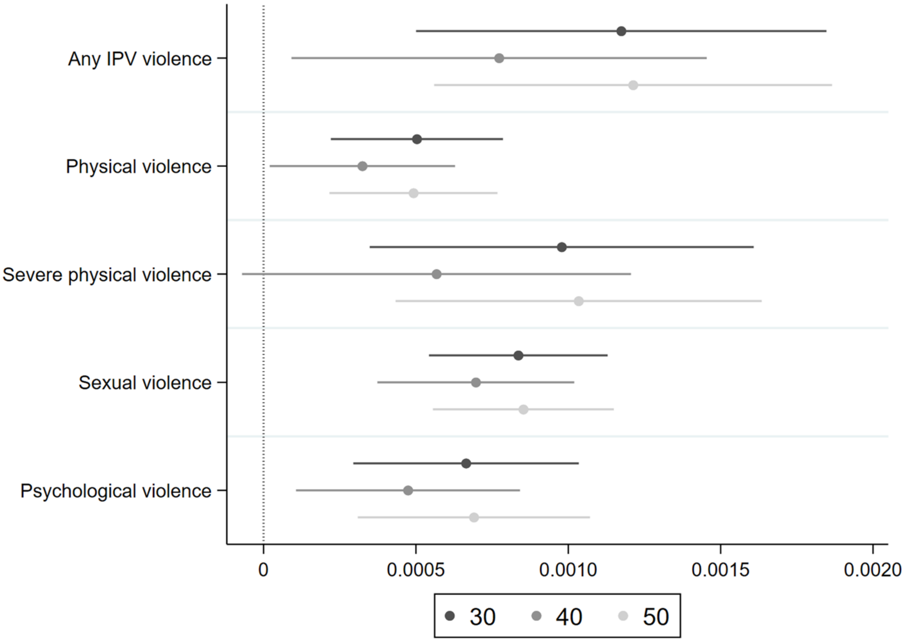

Fig. A9 Robustness tests for the geographical regions of 30, 40, and 50. *Note*: Coefficient plots are obtained from IV estimates. All regressions control for geographic region fixed effects, month of interview fixed effects, and year of survey fixed effects, individual and household level characteristics, and weather controls. Standard errors are clustered at the district level. The coefficients are represented by a small circle, while the 95% confidence interval is represented by a line

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Declarations

Conflict of interests The authors declare no competing interests.

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