Air Pollution and Intimate Partner Violence in India

[Working Paper]

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Abstract:

Rainfall variability and air pollution each pose significant risks of violence against women, with economic consequences in economies dependent on rainfed agriculture. Focusing on India, we combine individual-level data from the Demographic and Health Survey with high-resolution spatial data on climate and air pollutants to investigate how exposure to high levels of pollution influences spousal violence. For identification, we use atmospheric wind directions as an instrument for local pollution concentrations. We find that air pollution has a statistically significant impact on intimate partner violence, raising the incidence of physical violence by 4.3% (over the sample mean). Analysis of heterogeneous impacts suggests that our main results are driven by rural households and poor households. This is consistent with income stress mediating the effect of pollution on intimate partner violence. (JEL Classification: 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 depression (Balakrishnan and Tsaneva 2023; Lin et al. 2017; Chen, Oliva, and Zhang 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) and the United Kingdom (Bondy, Roth, and Sager 2020).

In this paper, we extend the evidence on the non-health effects of air pollution by examining to what extent 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 $10\mu g/m^3$), and especially, regions in the Indo-Gangetic plains (which also have the highest populated density in India) are exposed to as high as 16 times the levels set by the WHO standards (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.

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

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, spending more time indoors in an attempt to avoid air pollution (Jafarov, Singh, and Sahoo 2023) can lead to increased contact time between partners. Increased contact time, coupled with air pollution's effects on aggression (Berman et al. 2019) and reduced cognitive ability (Zhang, Chen, and Zhang 2018), can lead to more IPV. The indirect effect is due to 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, Kala, and Nyshadham 2022; Batheja 2023; Merfeld 2023). This can lead to income loss. Negative income shocks have been linked to IPV around the world (Cools, Flatø, and Kotsadam 2020; Abiona and Koppensteiner 2018; Bollman et al., n.d.). 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 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.

This article presents new evidence on how air pollution affects the incidence and intensity of intimate partner violence in a developing country context. 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 effect of pollution exposure in the six months prior to the survey on self-reported psychological, physical and sexual violence against women in India. The identification strategy relies on an instrumental variable (IV) set up to control for the possible presence of omitted variables that affect pollution and spousal violence. Following Balietti, Datta, and Veljanoska (2022), we use wind direction, defined at a regional level, as an instrument for air pollution.

We find that 10 $\mu g/m^3$ increase in PM2.5 is associated with a 4.3% increase in the incidence of IPV, specifically physical violence. Analysis of heterogeneous impacts suggests that the main results are driven by rural poor households, indicating that the income channel

[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 Crockett 2013).

(pollution-induced income stress) is a key mechanism. These findings are consistent with evidence suggesting that women are at the receiving end of violence triggered by environmental stressors including air pollution.

2. Conceptual Model

We present a simple single-pollutant model. The probability that a woman i living in an air pollution grid-cell c experiences intimate partner violence is given by

$$(1) \qquad y_i = f_i\big(PM_c, M_{i(h)}(PM_c), W_c, X_i, X_{i(h)}; \varepsilon_i\big),$$

Where PM_c is the average level of PM2.5 in the grid-cell in the past 6 months; $M_{i(h)}(PM_c)$ represents income stress that is associated with aggressive behavior; W_c represents a host of weather variables; X_i and $X_{i(h)}$ represent individual- and household-level characteristics; and ε_i are unobserved factors that influence the probability of a woman being exposed to violence. The identification assumption is that $E(Z_c, \varepsilon_i) = 0$, while $E(PM_c, \varepsilon_i) \neq 0$, where Z_c is an instrument for PM_c. Then, the effect of air pollution on intimate partner violence, y_i, conditional on ε_i, is

$$(2) \qquad \frac{dy_i}{dPM_c} = \frac{\partial f_i}{\partial PM_c} + \frac{\partial f_i}{\partial M_{i(h)}} \frac{\partial M_{i(h)}}{\partial PM_c},$$

Where the first element on the right-hand side of Eq. (1) shows the direct effect of air pollution on the outcome of interest. The direct effect of air pollution is on aggressive behavior through neuroinflammation and reduced serotonin production. The second term shows the indirect impact on the outcome of interest through the income stress channel. Pollution has a negative impact on output through labor supply and productivity, resulting in income loss, which is manifested in spousal violence.

3. 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.

3.1. 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 were interviewed for the Domestic Violence module. 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

[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 domestic violence.

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.

We focus our analysis on women who reported having experienced IPV in the past 12 months at the time of the survey. The responses to any domestic violence question could be “never”, “often”, “sometimes”, and “yes, but not in the last 12 months”. We believe that women who have been exposed to violence, even if it has not been in the past 12 months, are different from women who have never been exposed to violence. The problem with excluding these observations from the sample is that women may not have experienced one act of intimate partner violence in the past 12 months but may have been exposed to other violent acts in the past 12 months. By eliminating these observations from the sample, women who have been subjected to violence in the past 12 months may also be excluded completely. Therefore, to prevent the loss of these observations, though at the risk of introducing measurement error, we code 1 for these samples.

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 underreporting in the sample. Therefore, aggregating IPV data using any measure of IPV can potentially correct 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-years, husband age, husband education, type of residence, religion, social class, the household wealth index.

We restrict the sample of eligible women interviewed in the domestic violence module to women with non-missing information on these control variables. The final analysis sample is thus 59,073 women.

Importantly, DHS also collects the GPS locations of each cluster, enabling researchers to link DHS data set to other geo-coded data, including air pollution levels, precipitation, temperature, and wind speed and directions, at the cluster level.[4] 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 observe the interview month in the DHS data and use it to combine pollution data and other environmental variables for the past 12 months from the time of survey.

3.2. 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 (the six months prior to the date of interview)[5] are reported as a 1-hour temporal data with a horizontal resolution of 0.5 x 0.625 degrees grid. In our study area, there are 560 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

[4] 131 of the 28,526 geo-referenced clusters did not have GPS information and were not included in our sample.
[5] Sensitivity analyses are also performed using the past 3 and past 12 months as a study period of interest.

(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 monthly PM2.5 level during our study period is 50.48 $\mu g/m^3$, while the WHO recommended level is below 35 $\mu g/m^3$ (WHO 2021). The distribution of average PM2.5 in the past 6 months, as shown in Appendix Figure A2, suggests that there is sufficient variation in the 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.

3.3. 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 x 0.625 degrees grid and at hourly frequency (Global Modeling And Assimilation Office and Pawson 2015b). 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). Importantly for our identification strategy, to estimate the wind's direction, we divide the number of days the wind came from this direction by the total number of days throughout six months. Appendix Figure A3 shows that southeast wind days during winter closely correlate with pollution, while northwest winds correlate with the northwest during October through December. 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 bottom right panel of Appendix Figure A3).

3.4. Descriptive Statistics

Table 1 and 2 reports summary statistics for the analysis sample. Overall, 25.5% 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). Five percent 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. 33% of women have ever worked, out of which 27% were paid workers. Meanwhile, 23% of women are currently working. Less than three-quarters of females live in rural areas (as shown in Panel B of Table 1).

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. Our study area has 560 grid cells. The 6-month average PM2.5 level is 45.88 $\mu g/m^3$. Our study area has an average temperature 296.28 K, an average precipitation of 0.67 g/m^2s, and an average wind speed of 4.44 m/s.[6]

4. Econometric Approach

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

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

[6] The 6-month average PM2.5 level (45.88 $\mu g/m^3$) 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-months average precipitation (1.11 g/m^2s) is slightly higher than the 3- and 6-months averages (0.63 g/m^2s and 0.67 g/m^2s).

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 survey year y has experienced intimate partner violence in the last twelve months. 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. While domestic violence is measured over the previous 12-month period, we chose 6 months for the main pollution measure because women may be more likely to report more recent cases of domestic violence. In addition, pollution averaged over a longer time period may attenuate the effect of some months with extreme pollution. As a robustness check, we repeat the same analysis using various time scales for fine particulate matter PM2.5, including the past averages of 3 and 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 age (and age square) and husband 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), social class (an indicator of scheduled castes or scheduled tribes and of other backward castes), and the household wealth index (an indicator of poor households).

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 A5). We include a quadratic function of precipitation, temperature, and wind speed to capture non-linearities in the relationship between weather and pollution.

Following Balietti, Datta, and Veljanoska (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, v_{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 because women in these households (i.e., richer or more educated women) may also be less subject to violence. On the other hand, areas with higher pollution may be areas with more economic activity. Lower unemployment rates and higher incomes may be associated with lower domestic violence. This would then introduce a downward bias. In addition, the classical measurement error in the pollution variable and will bias $\widehat{\beta_1}$ downwards as well.

To address the endogeneity and omitted variable concerns, we use an instrumental variables approach. We chose wind directions, widely used in the economic literature (e.g., Balietti, Datta, and Veljanoska 2022; Bondy, Roth, and Sager 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 that wind originated from one of the four quadrant wind direction (north, east, south, and west) as our main explanatory variable.[7] We allow the impact of wind direction on local pollution to vary by geographical region. The estimating equation is:

$$(4) \qquad PM_{i(c,g)} = \gamma_0 + \sum_g^G \gamma_1^g Share_{ic}^N + \sum_g^G \gamma_2^g Share_{ic}^E + \sum_g^G \gamma_3^g Share_{ic}^S + W_{i(c,y)}\psi + X_i\xi + X_{i(h)}\lambda + \alpha_g + \eta_{i(m)} + \pi_{i(y)} + u_{icg}$$

$$(5) \quad y_{icgmy} = \beta_0 + \beta_1 \widehat{PM_{i(c,y)}} + W_{i(c,y)}\psi + X_i\xi + X_{i(h)}\lambda + \alpha_g + \eta_{i(m)} + \pi_{i(y)} + \varepsilon_{icgmy}$$

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.

[7] Using quadrant wind direction, we create the most common direction of the wind in a day. The wind direction is divided into four bins: [0-90], [90-180], [180-270], and [270-360]. Then we count the number of days in each bin over the past 6 months.

We follow Balietti, Datta, and Veljanoska (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, Datta, and Veljanoska (2022), we use 30 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, using a smaller number of regions, we may lose potentially useful variation in wind direction. Yet, we don't have a weak instrument problem as 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 28.9. Appendix Figure A4 further presents first-stage evidence to motivate our identification strategy. 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.

5. 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.

5.1. 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 percentage points (6.3% over the sample mean of 25.5%) 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 0.8 percentage point (or 6.5, 8.2, 13.0, and 7.8 percent) 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.

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

Using the average PM2.5 levels in the past 6 months would mask its nonlinear effect on incidence of intimate partner violence. PM2.5 levels that are low or moderate are between 0–35$\mu g/m^3$, and levels that are unhealthy are higher than 35$\mu g/m^3$. 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

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

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

Figure 1 displays the nonlinear effects of PM2.5 on incidence of any IPV. Results suggest that pollution levels between 35 and 44 $\mu g/m^3$ 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 0.04 and 0.05 percentage points respectively, while bin 5 and bin 6 are 0.10 and 0.09 percentage 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.

5.3. 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 most outcomes. For every 10 $\mu g/m^3$ increase in PM2.5, there is a 1.1 percentage point increase in probability of any type of IPV. This effect is 30% lower than the effect estimated using OLS, highlighting the upward bias of the OLS estimates likely due to household pollution avoidance behavior.

Even so, our analysis indicates that pollution has statistically and economically significant effects on intimate partner violence which ranges from 0.5 to 1.1 percentage points on average. This translates to an increase of 4.3% over the sample mean for any type of IPV, an increase of 4.2% in physical violence (and 8.2% in severe physical violence), and an increase of nearly 6% in psychological violence, and 1.7% 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 percent increase in domestic violence.

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

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.[8] 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.

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

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

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.

5.5. 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 examine the effect of pollution by area of residence. The results show that pollution has a very small (0.0002) and statistically insignificant effect on IPV for urban households while the effect for rural households is large (0.0016) and significant. 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.

One 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. Lower income for the family could increase the husband's stress, increasing the probability of domestic violence. 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. Additionally, lower income for women could also reduce female bargaining power and increase the probability of domestic violence. 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). We further test the plausibility of this income channel in Table 6 where we show that air pollution is statistically significantly associated with a lower likelihood of women working, women working in agriculture, as well as husbands working. Importantly, the negative effects on employment are only present in the rural sample and are small and not statistically significant for the urban sample. This provides support for the hypothesis that pollution may affect IPV through the income channel.

Another reason why we may see different effects of pollution on urban and rural households could be the difference in acceptability of domestic violence.[9] 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

[9] 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.

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 (0.0011 vs 0.0008), the two coefficients are not statistically significantly different from each other.

Next, we study heterogeneity by poverty status of the household.[10] We find that pollution has no effect on domestic violence among non-poor household but a strong, significant effect on poor households (0.0002 vs 0.0024). This is again consistent with the income mechanism as poor households are likely to be more affected by any income stress resulting from pollution's effect on productivity.

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 biological effect of pollution of IPV unlikely. Instead, our study provides suggestive evidence that the key mechanism through which pollution affects IPV is the indirect effect of the income stress. One caveat of our findings, however, is that we are unable to test for changes in time allocation, and specifically, more contact time between spouses resulting from higher pollution levels.

5.6. Robustness Checks

[10] 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.

Our main results are robust to a number of robustness checks. First, we perform checks on sample selection. In the main specification, the sample size is restricted to only married women. We test whether pollution affects the marital status of women, including women who are currently married, never married, and divorced/widowed out of those who have ever been married statistically differently. 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. We report these regression results in Table 7.

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, Datta, and Veljanoska (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 A8).

Finally, we 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 2 (as shown in Appendix Table A3).

6. 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 4.3% increase in the probability of women reporting domestic violence in the last 12 months. 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. This suggests that our main results are likely explained by income stress and not by the direct biological effect of neuroinflammation and increased aggression. Quantifying pollution externalities in developing countries context, where the baseline pollution concentrations are several times larger than those of developed countries and resources to mitigate them are limited, is important for targeted policy.

References

Abiona, Olukorede, and Martin Foureaux Koppensteiner. 2018. "The Impact of Household Shocks on Domestic Violence: Evidence from Tanzania." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3301756.

Adams, Abi, Kristiina Huttunen, Emily Nix, and Ning Zhang. 2024. "The Dynamics of Abusive Relationships." *The Quarterly Journal of Economics* 139 (4): 2135–80. https://doi.org/10.1093/qje/qjae022.

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham. 2022. "Management and Shocks to Worker Productivity." *Journal of Political Economy* 130 (1): 1–47. https://doi.org/10.1086/717046.

Aguilar-Gomez, Sandra, Holt Dwyer, Joshua Graff Zivin, and Matthew Neidell. 2022. "This Is Air: The 'Nonhealth' Effects of Air Pollution." *Annual Review of Resource Economics* 14 (1): 403–25. https://doi.org/10.1146/annurev-resource-111820-021816.

Angelucci, Manuela. 2008. "Love on the Rocks: Domestic Violence and Alcohol Abuse in Rural Mexico." *The B.E. Journal of Economic Analysis & Policy* 8 (1). https://doi.org/10.2202/1935-1682.1766.

Balakrishnan, Uttara, and Magda Tsaneva. 2023. "Impact of Air Pollution on Mental Health in India." *The Journal of Development Studies* 59 (1): 133–47. https://doi.org/10.1080/00220388.2022.2120804.

Balietti, Anca, Souvik Datta, and Stefanija Veljanoska. 2022. "Air Pollution and Child Development in India." *Journal of Environmental Economics and Management* 113 (May):102624. https://doi.org/10.1016/j.jeem.2022.102624.

Batheja, Deepshikha. 2023. "More than Particulate Matters: Pollution and Productivity in Indian Call Centers." https://doi.org/10.26085/C3HC7C.

Berman, Jesse D., Jesse Burkhardt, Jude Bayham, Ellison Carter, and Ander Wilson. 2019. "Acute Air Pollution Exposure and the Risk of Violent Behavior in the United States." *Epidemiology* 30 (6): 799–806. https://doi.org/10.1097/EDE.0000000000001085.

Bhalotra, Sonia, Uma Kambhampati, Samantha Rawlings, and Zahra Siddique. 2021. "Intimate Partner Violence: The Influence of Job Opportunities for Men and Women." *The World Bank Economic Review* 35 (2): 461–79. https://doi.org/10.1093/wber/lhz030.

Bhuller, Manudeep, Gordon B. Dahl, Katrine V. Løken, and Magne Mogstad. 2024. "Domestic Violence Reports and the Mental Health and Well-Being of Victims and Their Children." *Journal of Human Resources* 59 (S): S152–86. https://doi.org/10.3368/jhr.1222-12698R1.

Bollman, Katie, Judhajit Chakraborty, Leah Lakdawala, and Eduardo Nakasone. n.d. "Frosty Climate, Icy Relationships: Frosts and Intimate Partner Violence in Rural Peru."

Bondy, Malvina, Sefi Roth, and Lutz Sager. 2020. "Crime Is in the Air: The Contemporaneous Relationship between Air Pollution and Crime." *Journal of the Association of Environmental and Resource Economists* 7 (3): 555–85. https://doi.org/10.1086/707127.

Braun, Mark, and Sofia B. Villas-Boas. 2023. "Pollution and Fatal Traffic Accidents in California Counties." *Applied Economic Perspectives and Policy*, September, aepp.13396. https://doi.org/10.1002/aepp.13396.

Burkhardt, Jesse, Jude Bayham, Ander Wilson, Ellison Carter, Jesse D. Berman, Katelyn O'Dell, Bonne Ford, Emily V. Fischer, and Jeffrey R. Pierce. 2019. "The Effect of Pollution on Crime: Evidence from Data on Particulate Matter and Ozone." *Journal of Environmental Economics and Management* 98 (November):102267. https://doi.org/10.1016/j.jeem.2019.102267.

Chang, Harrison, Shiau-Fang Chao, Kuan-Ming Chen, and Ming-Jen Lin. 2023. "When Love Hurts: The Impact of Intimate Partner Violence on Later Life Outcomes." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4475647.

Chen, Shuai, Paulina Oliva, and Peng Zhang. 2024. "Air Pollution and Mental Health: Evidence from China." *AEA Papers and Proceedings* 114 (May):423–28. https://doi.org/10.1257/pandp.20241062.

Coccaro, Emil F., Chandra Sekhar Sripada, Rachel N. Yanowitch, and K. Luan Phan. 2011. "Corticolimbic Function in Impulsive Aggressive Behavior." *Biological Psychiatry* 69 (12): 1153–59. https://doi.org/10.1016/j.biopsych.2011.02.032.

Cools, Sara, Martin Flatø, and Andreas Kotsadam. 2020. "Rainfall Shocks and Intimate Partner Violence in Sub-Saharan Africa." *Journal of Peace Research* 57 (3): 377–90. https://doi.org/10.1177/0022343319880252.

Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif. 2019. "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction." *American Economic Review* 109 (12): 4178–4219. https://doi.org/10.1257/aer.20180279.

Global Modeling And Assimilation Office, and Steven Pawson. 2015a. "MERRA-2 tavg1_2d_aer_Nx: 2d,1-Hourly,Time-Averaged,Single-Level,Assimilation,Aerosol Diagnostics V5.12.4." NASA Goddard Earth Sciences Data and Information Services Center. https://doi.org/10.5067/KLICLTZ8EM9D.

———. 2015b. "MERRA-2 tavg1_2d_flx_Nx: 2d,1-Hourly,Time-Averaged,Single-Level,Assimilation,Surface Flux Diagnostics V5.12.4." NASA Goddard Earth Sciences Data and Information Services Center. https://doi.org/10.5067/7MCPBJ41Y0K6.

González, Libertad, and Núria Rodríguez-Planas. 2020. "Gender Norms and Intimate Partner Violence." *Journal of Economic Behavior & Organization* 178 (October):223–48. https://doi.org/10.1016/j.jebo.2020.07.024.

Herrnstadt, Evan, Anthony Heyes, Erich Muehlegger, and Soodeh Saberian. 2021. "Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago." *American Economic Journal: Applied Economics* 13 (4): 70–100. https://doi.org/10.1257/app.20190091.

Hoek, Gerard, Ranjini M Krishnan, Rob Beelen, Annette Peters, Bart Ostro, Bert Brunekreef, and Joel D Kaufman. 2013. "Long-Term Air Pollution Exposure and Cardio- Respiratory Mortality: A Review." *Environmental Health* 12 (1): 43. https://doi.org/10.1186/1476-069X-12-43.

Jafarov, Jafar, Tejendra Pratap Singh, and Soham Sahoo. 2023. "Air Pollution and Time Use: Evidence from India." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4614725.

Lelieveld, J., J. S. Evans, M. Fnais, D. Giannadaki, and A. Pozzer. 2015. "The Contribution of Outdoor Air Pollution Sources to Premature Mortality on a Global Scale." *Nature* 525 (7569): 367–71. https://doi.org/10.1038/nature15371.

Lin, Hualiang, Yanfei Guo, Paul Kowal, Collins O. Airhihenbuwa, Qian Di, Yang Zheng, Xing Zhao, et al. 2017. "Exposure to Air Pollution and Tobacco Smoking and Their Combined Effects on Depression in Six Low- and Middle-Income Countries." *British Journal of Psychiatry* 211 (3): 157–62. https://doi.org/10.1192/bjp.bp.117.202325.

Menon, Seetha. 2020. "The Effect of Marital Endowments on Domestic Violence in India." *Journal of Development Economics* 143 (March):102389. https://doi.org/10.1016/j.jdeveco.2019.102389.

Merfeld, Joshua D. 2023. "Air Pollution and Agricultural Productivity in a Developing Country." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4483694.

Miller, Kristin A., David S. Siscovick, Lianne Sheppard, Kristen Shepherd, Jeffrey H. Sullivan, Garnet L. Anderson, and Joel D. Kaufman. 2007. "Long-Term Exposure to Air Pollution and Incidence of Cardiovascular Events in Women." *New England Journal of Medicine* 356 (5): 447–58. https://doi.org/10.1056/NEJMoa054409.

Murphy, S E, R Norbury, B R Godlewska, P J Cowen, Z M Mannie, C J Harmer, and M R Munafò. 2013. "The Effect of the Serotonin Transporter Polymorphism (5-HTTLPR) on Amygdala Function: A Meta-Analysis." *Molecular Psychiatry* 18 (4): 512–20. https://doi.org/10.1038/mp.2012.19.

Panda, Pradeep, and Bina Agarwal. 2005. "Marital Violence, Human Development and Women's Property Status in India." *World Development* 33 (5): 823–50. https://doi.org/10.1016/j.worlddev.2005.01.009.

Paz, Carlos, and Salvador Huitrón-Reséndiz. 1996. "The Effects of Ozone Exposure on the Sleep-Wake Cycle and Serotonin Contents in the Pons of the Rat." *Neuroscience Letters* 204 (1–2): 49–52. https://doi.org/10.1016/0304-3940(96)12313-2.

Provençal, Simon, Virginie Buchard, Arlindo M. Da Silva, Richard Leduc, Nathalie Barrette, Emily Elhacham, and Sheng-Hsiang Wang. 2017. "Evaluation of PM2.5 Surface Concentrations Simulated by Version 1 of NASA's MERRA Aerosol Reanalysis over Israel and Taiwan." *Aerosol and Air Quality Research* 17 (1): 253–61. https://doi.org/10.4209/aaqr.2016.04.0145.

Ravishankara, A. R., Liji M. David, Jeffrey R. Pierce, and Chandra Venkataraman. 2020. "Outdoor Air Pollution in India Is Not Only an Urban Problem." *Proceedings of the National Academy of Sciences* 117 (46): 28640–44. https://doi.org/10.1073/pnas.2007236117.

Sekhri, Sheetal, and Adam Storeygard. 2014. "Dowry Deaths: Response to Weather Variability in India." *Journal of Development Economics* 111 (November):212–23. https://doi.org/10.1016/j.jdeveco.2014.09.001.

Siegel, Jenifer Z., and Molly J. Crockett. 2013. "How Serotonin Shapes Moral Judgment and Behavior." *Annals of the New York Academy of Sciences* 1299 (1): 42–51. https://doi.org/10.1111/nyas.12229.

WHO. 2021. "WHO Global Air Quality Guidelines. Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide. Executive Summary." Geneva: World Health Organization. https://iris.who.int/bitstream/handle/10665/345334/9789240034433-eng.pdf.

Zhang, Xin, Xi Chen, and Xiaobo Zhang. 2018. "The Impact of Exposure to Air Pollution on Cognitive Performance." *Proceedings of the National Academy of Sciences* 115 (37): 9193–97. https://doi.org/10.1073/pnas.1809474115.

Tables and Figures

Table 1. Individual- and household-level summary statistics (N = 59,073)

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				
Physical/sexual violence	0.586	1.403	0	10
Physical violence	0.495	1.165	0	7
Psychological violence	0.168	0.551	0	3
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

Notes: The sample is restricted to only women who are selected and interviewed for the Domestic Violence module.
[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 cell = 560)

Variable	Mean	SD	Min	Max
Panel A: Particulate matter ($\mu g/m^3$)				
PM2.5 last 6 months	45.868	18.380	5.655	102.393
Pollution bin:				
[5,35)	0.284	0.410	0	1
[35,45)	0.285	0.385	0	1
[45,55)	0.171	0.298	0	1
[55,65)	0.102	0.245	0	1
[65,75)	0.054	0.163	0	1
[>75]	0.103	0.268	0	1
Panel B: Proportion of winds in the last 6 months that originated from this direction:				
North	0.274	0.179	0	0.718
East	0.298	0.218	0	0.857
South	0.216	0.160	0	0.923
West	0.212	0.151	0	0.852
Panel C: Weather in the past 6 months prior to the interview				
Mean temperature (K)	296.282	5.981	262.764	303.212
Total precipitation (g/m^2s)	0.666	1.176	0	9.466
Wind speed (m/s)	4.438	0.803	2.454	6.988

Notes: 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 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 [1]	Physical violence [2]	Severe physical violence [3]	Sexual violence [4]	Psychological violence [5]
Panel A: OLS estimates					
PM2.5 ($\mu g/m^3$)	0.0016***	0.0014***	0.0005**	0.0007***	0.0008***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Panel B: IV estimates using wind directions					
PM2.5 ($\mu g/m^3$)	0.0011***	0.0009***	0.0005***	0.0009***	0.0006***
	(0.0004)	(0.0003)	(0.0001)	(0.0002)	(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)	28.902	28.902	28.902	28.902	28.902
Observations	59,073	59,073	59,073	59,073	59,073
Adj. R-squared	0.043	0.042	0.022	0.010	0.016

Notes:

[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 A2 report the regression results from the first stage.

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

Dependent variable: Count of violence	Any IPV	Physical/sexual violence	Physical violence	Psychological violence
	[1]	[2]	[3]	[4]
Panel A: Maximum Likelihood Poisson estimates				
PM2.5 ($\mu g/m^3$)	0.0075^{***}	0.0071^{***}	0.0070^{***}	0.0071^{***}
	(0.0013)	(0.0013)	(0.0013)	(0.0015)
Panel B: Maximum Likelihood Control Function Poisson estimates				
PM2.5 ($\mu g/m^3$)	0.0063^{***}	0.0059^{***}	0.0058^{***}	0.0065^{***}
	(0.0017)	(0.0018)	(0.0018)	(0.0018)
First-stage residuals	0.0031	0.0032	0.0037	0.0028
	(0.0030)	(0.0032)	(0.0032)	(0.0031)
Geographic regions FEs	Yes	Yes	Yes	Yes
Month of interview FEs	Yes	Yes	Yes	Yes
Survey year FEs	Yes	Yes	Yes	Yes
Observations	59,073	59,073	59,073	59,073
Pseudo R squared	0.080	0.078	0.073	0.046
Log likelihood	-86443.706	-70909.257	-61768.916	-29218.991

Notes:

[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. See Table 3 for more details. For the purpose of obtaining standard errors in Column 3, we exclude household-level characteristics from the Poisson estimates.

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

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

[5] Appendix Table A2 report the regression results from the first stage.

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	0.0011***	28.902	0.0063***	0.0031
	(0.0004)	[59,073]	(0.0017)	[59,073]
Rural household sample	0.0016***	31.048	0.0090***	0.0007
	(0.0004)	[41,743]	(0.0018)	[41,743]
Urban household sample	0.0002	27.444	-0.0023	0.0105**
	(0.0005)	[17,330]	(0.0028)	[17,330]
Poor household sample	0.0024***	25.362	0.0119***	-0.0068**
	(0.0005)	[23,851]	(0.0018)	[23,851]
Non-poor household sample	0.0002	31.314	-0.0011	0.0180***
	(0.0004)	[35,222]	(0.0025)	[35,222]
Wife beating justified sample	0.0011**	25.462	0.0055***	0.0015
	(0.0004)	[29,699]	(0.0018)	[29,699]
Wife beating not justified sample	0.0008**	32.581	0.0071***	0.0040
	(0.0004)	[29,374]	(0.0027)	[29,374]
Estimates	IV		Control Function Poisson	

Notes:
[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**.

Table 6. Possible Mechanisms

	Woman currently works [1]	Woman works in agricultural sector [2]	Husband currently works [3]
Panel A: All residences (both rural and urban)			
PM2.5 ($\mu g/m^3$)	-0.0022***	-0.0025***	-0.0006***
	(0.0004)	(0.0004)	(0.0002)
Mean of dependent var.	0.319	0.170	0.949
Observations	59,073	59,073	59,073
F-stat	28.902	28.902	28.902
Panel B: Only rural residence			
PM2.5 ($\mu g/m^3$)	-0.0031***	-0.0034***	-0.0008***
	(0.0005)	(0.0005)	(0.0002)
Mean of dependent var.	0.352	0.225	0.953
Observations	41,743	41,743	41,743
F-stat	31.048	31.048	31.048
Panel C: Only urban residence			
PM2.5 ($\mu g/m^3$)	0.0001	0.0002	0.00002
	(0.0005)	(0.0003)	(0.0003)
Mean of dependent var.	0.239	0.039	0.940
Observations	17,330	17,330	17,330
F-stat	27.444	27.444	27.444

Notes: 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.

Table 7. Robustness Checks

Dependent variable: Binary (0/1)	Sample selection		
	Currently married [1]	Never married [2]	Divorced /widowed [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	75,364	75,364	62,588
F-stat	28.499	28.499	28.718

Notes: 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<0.01*** and p<0.10*.

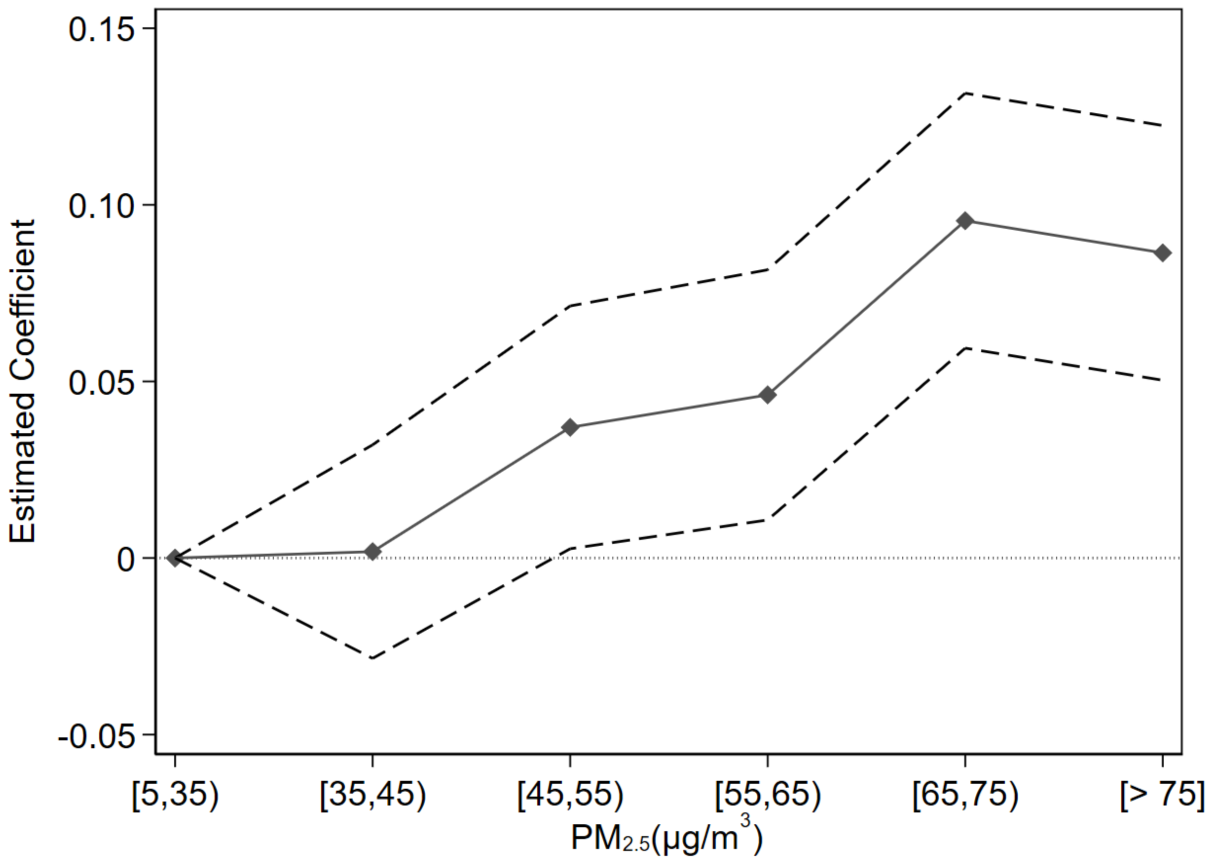

Figure 1. Nonlinear Effects of PM2.5 on Incidence of Intimate Partner Violence.

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 A1 for full results.

Appendix A: Additional Tables and Figures

Table A1. Non-linear effects of PM2.5 on the incidence of IPV

	Any IPV violence
Pollution bin: [5,35) is used as reference	
[35,45)	0.0018
	(0.0154)
[45,55)	0.0370**
	(0.0175)
[55,65)	0.0462**
	(0.0181)
[65,75)	0.0955***
	(0.0184)
[>75]	0.0864***
	(0.0184)
Geographical regions FEs	Yes
Month of interview FEs	Yes
Survey year FEs	Yes
Observations	59,073
Adj. R-squared	0.069

Notes: 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 A2. First-stage regression results.

	(1) pm25_6mon_exp
Share of the wind from the North, region 1	-52.25***
	(-3.86)
Share of the wind from the North, region 2	-70.53***
	(-5.27)
Share of the wind from the North, region 3	-21.50*
	(-2.48)
Share of the wind from the North, region 4	136.2***
	(5.22)
Share of the wind from the North, region 5	-34.66**
	(-2.93)
Share of the wind from the North, region 6	-25.88***
	(-4.77)
Share of the wind from the North, region 7	-6.524
	(-0.74)
Share of the wind from the North, region 8	-22.30***
	(-4.27)
Share of the wind from the North, region 9	-17.40
	(-1.11)
Share of the wind from the North, region 10	-15.15
	(-1.38)
Share of the wind from the North, region 11	-51.92***
	(-6.06)
Share of the wind from the North, region 12	-4.577
	(-0.39)
Share of the wind from the North, region 13	-61.80***
	(-4.16)
Share of the wind from the North, region 14	120.2
	(1.04)
Share of the wind from the North, region 15	-40.24***
	(-3.66)
Share of the wind from the North, region 16	-64.15***
	(-7.08)
Share of the wind from the North, region 17	16.65
	(0.93)
Share of the wind from the North, region 18	-51.14**
	(-2.81)
Share of the wind from the North, region 19	-45.82
	(-1.17)
Share of the wind from the North, region 20	-8.361
	(-1.92)
Share of the wind from the North, region 21	-68.48**
	(-3.02)
Share of the wind from the North, region 22	-6.613
	(-1.08)
Share of the wind from the North, region 23	-47.52***

	(-6.31)
Share of the wind from the North, region 24	-25.41
	(-1.81)
Share of the wind from the North, region 25	7.232
	(0.34)
Share of the wind from the North, region 26	-32.96***
	(-4.50)
Share of the wind from the North, region 27	-63.53***
	(-3.78)
Share of the wind from the North, region 28	-9.852
	(-0.22)
Share of the wind from the North, region 29	-10.42
	(-1.06)
Share of the wind from the North, region 30	-54.88**
	(-2.58)
Share of the wind from the East, region 1	18.61
	(1.74)
Share of the wind from the East, region 2	-2.678
	(-0.23)
Share of the wind from the East, region 3	46.99***
	(6.79)
Share of the wind from the East, region 4	94.86***
	(7.50)
Share of the wind from the East, region 5	3.294
	(0.24)
Share of the wind from the East, region 6	39.21***
	(7.31)
Share of the wind from the East, region 7	30.80***
	(5.13)
Share of the wind from the East, region 8	-1.765
	(-0.48)
Share of the wind from the East, region 9	25.82*
	(2.33)
Share of the wind from the East, region 10	39.08***
	(3.84)
Share of the wind from the East, region 11	-2.076
	(-0.24)
Share of the wind from the East, region 12	11.11
	(0.89)
Share of the wind from the East, region 13	26.98*
	(2.07)
Share of the wind from the East, region 14	121.8**
	(3.01)
Share of the wind from the East, region 15	38.42***
	(3.43)
Share of the wind from the East, region 16	-7.238
	(-0.75)
Share of the wind from the East, region 17	34.33*
	(2.03)
Share of the wind from the East, region 18	41.26**

	(2.68)
Share of the wind from the East, region 19	-28.10
	(-0.76)
Share of the wind from the East, region 20	33.06***
	(8.05)
Share of the wind from the East, region 21	62.50***
	(8.79)
Share of the wind from the East, region 22	9.697*
	(2.11)
Share of the wind from the East, region 23	14.65
	(1.66)
Share of the wind from the East, region 24	5.923
	(0.58)
Share of the wind from the East, region 25	117.3***
	(8.21)
Share of the wind from the East, region 26	-5.903
	(-1.37)
Share of the wind from the East, region 27	-6.645
	(-0.87)
Share of the wind from the East, region 28	20.81
	(0.64)
Share of the wind from the East, region 29	109.2***
	(3.73)
Share of the wind from the East, region 30	14.81
	(1.19)
Share of the wind from the South, region 1	38.47**
	(2.58)
Share of the wind from the South, region 2	0.0301
	(0.00)
Share of the wind from the South, region 3	21.77*
	(2.13)
Share of the wind from the South, region 4	59.16***
	(5.62)
Share of the wind from the South, region 5	8.795
	(0.67)
Share of the wind from the South, region 6	7.102
	(1.16)
Share of the wind from the South, region 7	21.48*
	(2.46)
Share of the wind from the South, region 8	34.83***
	(11.62)
Share of the wind from the South, region 9	-13.12
	(-1.22)
Share of the wind from the South, region 10	19.81
	(1.37)
Share of the wind from the South, region 11	-6.362
	(-0.50)
Share of the wind from the South, region 12	5.161
	(0.35)
Share of the wind from the South, region 13	22.18

	(1.03)
Share of the wind from the South, region 14	125.0**
	(3.04)
Share of the wind from the South, region 15	17.16
	(1.64)
Share of the wind from the South, region 16	-1.503
	(-0.12)
Share of the wind from the South, region 17	28.88
	(1.53)
Share of the wind from the South, region 18	-7.622
	(-0.48)
Share of the wind from the South, region 19	-75.77*
	(-2.03)
Share of the wind from the South, region 20	13.31**
	(2.99)
Share of the wind from the South, region 21	9.549
	(0.98)
Share of the wind from the South, region 22	23.07***
	(3.41)
Share of the wind from the South, region 23	19.50
	(1.58)
Share of the wind from the South, region 24	26.83
	(1.48)
Share of the wind from the South, region 25	89.03***
	(5.30)
Share of the wind from the South, region 26	52.30***
	(5.25)
Share of the wind from the South, region 27	27.94**
	(2.77)
Share of the wind from the South, region 28	60.00*
	(2.18)
Share of the wind from the South, region 29	34.50***
	(3.83)
Share of the wind from the South, region 30	13.87
	(0.51)
Individual-level characteristics	
Woman's current age	0.0349
	(0.68)
Woman's age square	-0.000746
	(-1.22)
Woman's education:	
No education	0.776**
	(3.05)
Primary education	0.377
	(1.57)
Incomplete secondary education	0.440*
	(2.37)
Secondary education	0.391*
	(2.00)
Number of children under 5	-0.0237
	(-0.45)

Husband's education:	
No education	0.234
	(1.07)
Primary education	0.206
	(1.00)
Secondary education	0.00634
	(0.04)
Husband age	-0.0307
	(-0.71)
Husband age square	0.000353
	(0.89)
Household-level characteristics	
Rural	0.0912
	(0.39)
Religion (Hindu = 1)	-1.100*
	(-2.36)
Social class (SC/ST = 1)	0.638
	(1.74)
Social class (OBC = 1)	1.108***
	(3.74)
Household wealth index:	
Poor	-0.397
	(-1.38)
Middle	-0.362*
	(-2.11)
Mean temperature	18.35***
	(4.08)
Mean temperature square	-0.0288***
	(-3.67)
Total precipitation	-1.172
	(-0.95)
Total precipitation square	0.295*
	(2.11)
Wind speed	40.85***
	(7.88)
Wind speed square	-4.691***
	(-8.33)
Geographical regions FEs	Yes
Month of interview FEs	Yes
Survey year FEs	Yes
Observations	59,073
Adj. R-squared	0.043

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

Table A3. 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 [1]	Physical violence [2]	Severe physical violence [3]	Sexual violence [4]	Psychological violence [5]
Panel A: PM2.5 last 3 months					
PM2.5 ($\mu g/m^3$)	0.0009***	0.0007*	0.0002	0.0007***	0.0002
	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0002)
F-stat	14.137	14.137	14.137	14.137	14.137
Panel B: PM2.5 last 12 months					
PM2.5 ($\mu g/m^3$)	0.0011*	0.0009*	0.0005**	0.0011***	0.0009***
	(0.0006)	(0.0005)	(0.0002)	(0.0002)	(0.0003)
F-stat	29.686	29.686	29.686	29.686	29.686
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	59,073	59,073	59,073	59,073	59,073

Notes:

[1] All regressions include individual and household controls, as well as weather controls. See Table 2 for more details.

[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.

[4] Appendix Table A1 report the regression results from the first stage.

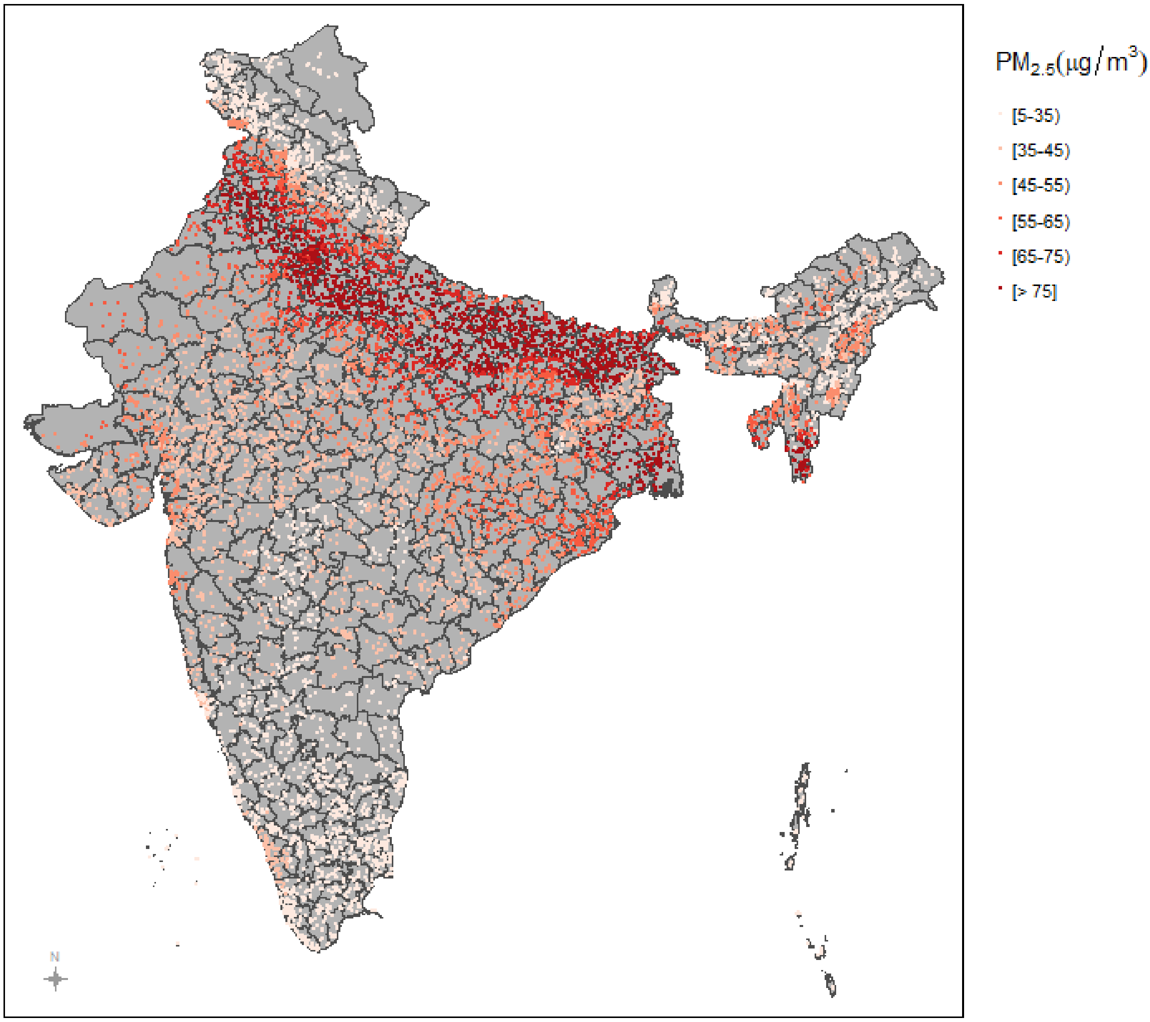

Figure A1. Map of the Study Area

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.

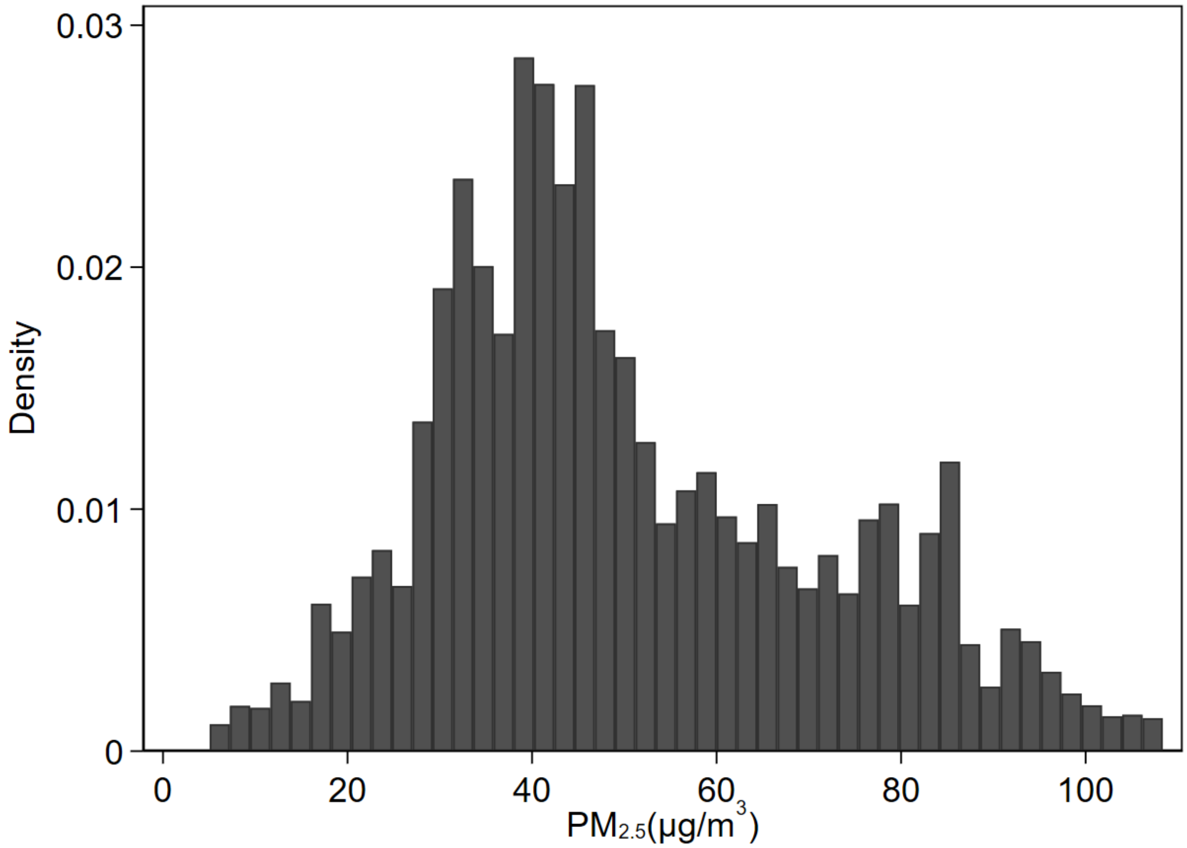

Figure A2. Distribution of PM2.5 concentration levels.

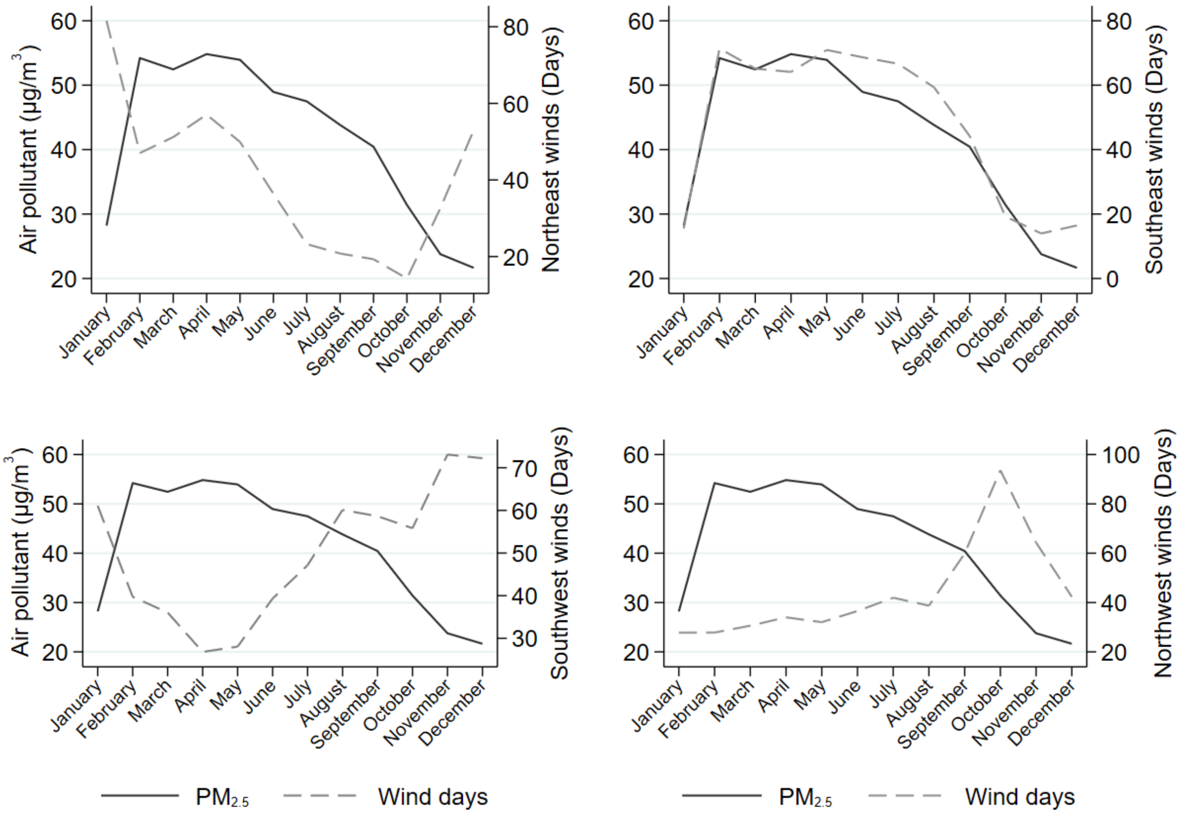

Figure A3. Time Trend of PM2.5 and Wind days.

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.

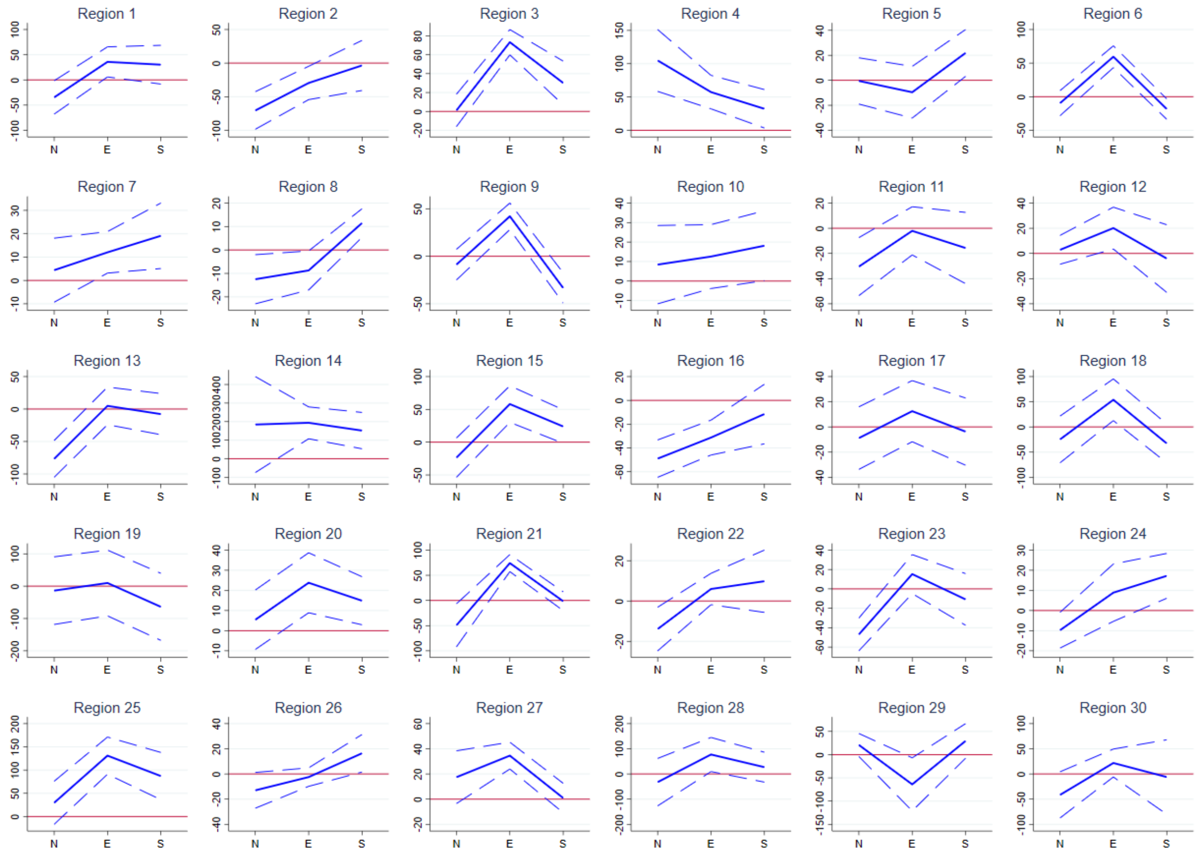

Figure A4. Semi-annual wind direction and PM2.5: first stage estimates by regions.

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.

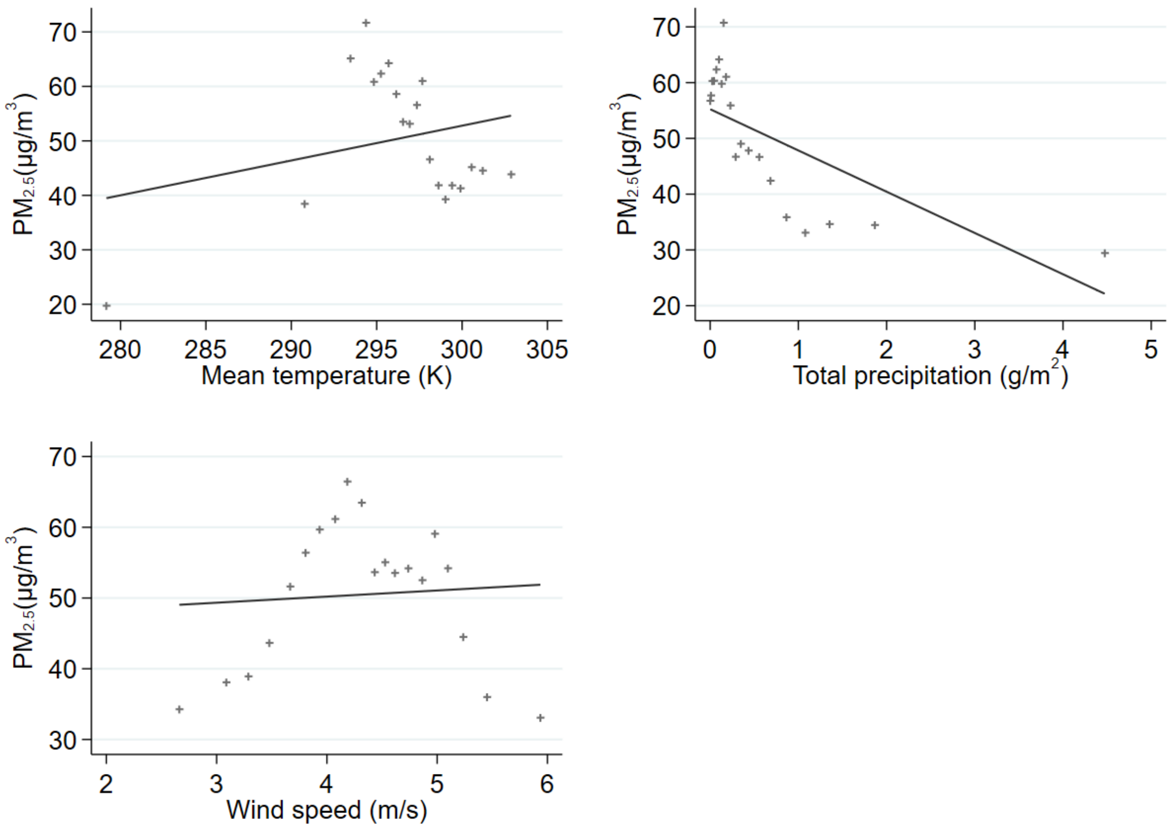

Figure A5. PM2.5 and Weather Bin Scatterplot.

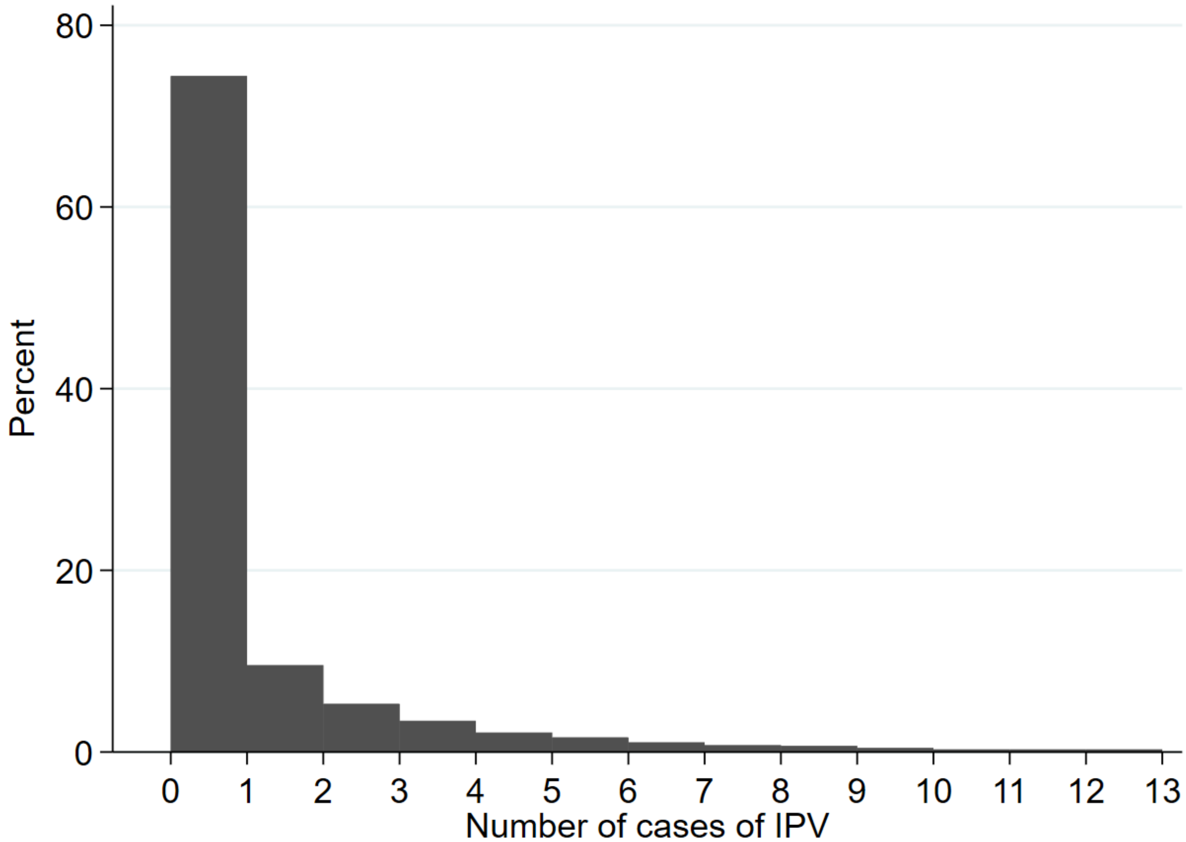

Figure A6. Distribution of cases of intimate partner violence.

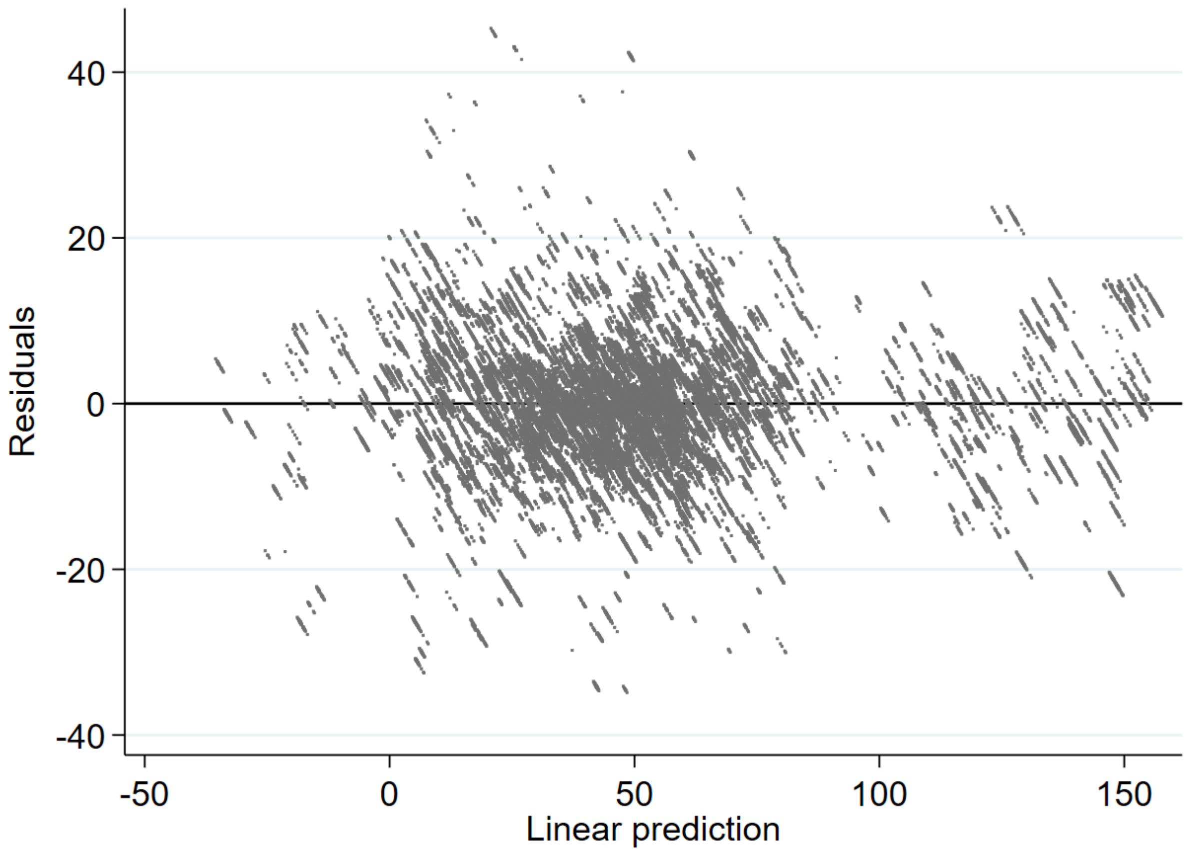

Figure A7. Scatter plot of residuals from the first stage of the control function approach.

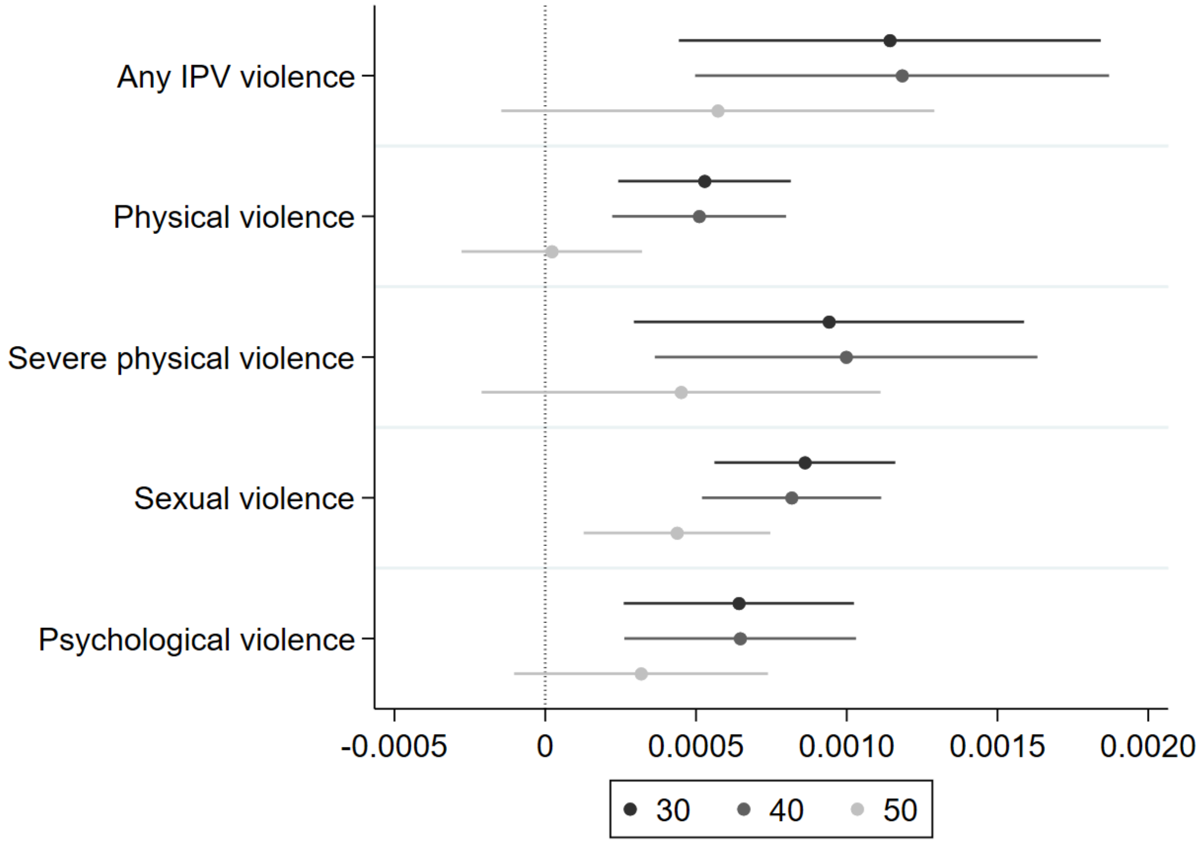

Figure A8. Robustness tests for the geographical regions of 30, 40, and 50.

Notes: Coefplots 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.